ALIGNING DEMAND FOR SPARE PARTS
WITH THEIR
UNDERLYING FAILURE MODES

THESIS

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Requirements for the Degree of

Master of Science in Logistics Management

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Acknowledgments

The purpose of this study was to determine if demands or maintenance actions are correlated to operational characterisitics of the weapon system at the specific work unit code level. The results of this research may help Air Force logisticians predict reparable spares demand with a greater degree of certainty, which could improve overall operational effectiveness while also saving constrained Air Force budget dollars.

Historical literature focusing on demand forecasting problems was reviewed to achieve an understanding of the inherent problems in aligning weapon system failures with demands. F-15C databases from 1993 and 1994 were used as input data and the methodology focused on developing multiple or Poisson regression forecasting models or a suitable Poisson process estimation technique.

This research could not have been completed without the assistance of several people. We are deeply indebted to our advisors, Major Terrance Pohlen and Major Lee Lehmkuhl, for keeping us motivated and on the right path. Our thesis reader, Dr. Dan Reynolds, was also a key player by ensuring our statistical analysis was sound.

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Most of all, we are thankful for our wives and families who stood by us every step of the way in fulfilling this thesis research and living the AFIT experience.

Steven D. Kephart Richard C. Roberts

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List of Acronyms

AFMC -- Air Force Materiel Command
AOR -- area of responsibility
CAMS -- Consolidated Aircraft Maintenance System
CUMFH -- cumulative flying hours
CUMFH2 -- cumulative flying hours squared
CUMFHNSORT -- cumulative flying hours times number of sorties
D029 -- WRSK Requirements Computation System
D041 -- Recoverable Consumption Item Requirements System
DLR -- depot level reparable
ECM -- electronic counter measure
ERRC -- expendability, recoverability, repairability category
FHNSORT -- cumulative flying hours times number of sorties
FMC -- fully mission capable
ICT -- integrated combat turn
LMI -- Logistics Management Institute
LRU -- line-replaceable unit
MDS -- mission design series
METRIC -- Multi-EchelonTechnique for Recoverable Item Control
MRSP -- mobility readiness spares package
NOP -- non-optimized items
NSORT -- number of sorties
NSORT2 -- number of sorties squared
O & M -- operations and maintenance
PBR -- percentage of base repair
RAPS -- Rotable Allocation and Planning System
REALM -- Requirements/Execution Availability Logistics Module
REMIS -- Reliability and Maintainability Information System
RRR -- remove/repair/replace
SAS -- Statistical Analysis System
SRAN -- stock record account number
SRU -- shop replaceable unit
TAIL -- aircraft tail number
VTMR -- variance-to-mean ratio
WMP -- war and mobilization plan
WRSK -- war readiness spares kit
WSMIS -- Weapon System Management Information System
WUC -- work unit code

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Abstract

Current Air Force demand forecasting systems, D041 and REALM, which are used to compute reparable authorizations and Mobility Readiness Spares Package configuration quantities, assume demand is driven solely on a flying hour basis. The purpose of this study was to evaluate the relationship between reparable demands, flying hours, and number of sorties. This study is unique because it analyzes the demand, flying hour, sortie relationship at the work unit code level, in an attempt to improve reparable demand forecasting. A three phase methodology is used as the basis for the work unit code level analysis.

The first phase used multiple linear regression to determine a relationship at various levels of the work unit code. Multiple linear regression provided limited correlation between demands, flying hours, and sorties at the work unit code level. Any resulting multiple regression models provided poor estimates of expected demands when a residual analysis was performed against a validation data set.

The second phase used Poisson regression to evaluate the integer, count nature of the demands variable used in the analysis. The Poisson regression results also exhibited poor correlation between demands, flying hours, and number of sorties at the work unit code level.

The third phase fitted a Poisson process to the data in the study. The Poisson process did produce better results than multiple or Poisson regression. However, the Poisson process performed poorly in estimating future demands at the work unit code level, based on historical flying hour and sortie driven demand rate occurrences.

The results of this study support previous demand forecasting research which has

been unable to demonstrate an accurate demand forecasting relationship between demands, flying hours, and number of sorties. Nevertheless, follow-on work unit code level research is suggested with a larger data set. Also, variables other than flying hours and sorties should be considered to evaluate the erratic, uncertain nature of reparable demand forecasting.

ALIGNING DEMAND FOR SPARE PARTS

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I. Introduction

Military aircraft, like other Department of Defense assets, experience failures of their component parts. Major problems faced in forecasting demand for aircraft reparable spare parts are the uncertainties in determining exactly "When?" spares will fail and "What quantities?" need to be ordered to support a weapon system over a specified timeframe. If spares failures and subsequent demand forecasts could be predicted with certainty, the United States Air Force would procure and stock only the required number of assets to support assigned weapon systems. However, failures of aircraft spares are uncertain in nature and the Air Force stocks large quantities of spares to protect against this uncertainty in the system.

Accurate forecasting of reparable spare quantities is definitely important in a peacetime environment to attain mission readiness and minimize operational costs. However, accurate spares forecasting plays an even more critical role in a wartime environment. War readiness spares are authorized in configurations known as Mobility Readiness Spares Packages (MRSPs). MRSP spare quantities are limited to established wartime authorizations and the overall capacity limitations of the deployable bins, which comprise the MRSP. Due to these limitations, accurate and reliable MRSP spares forecasts become a crucial logistical objective and are necessary to ensure vital tactical and strategic objectives are achieved.

In order to accurately forecast peacetime and MRSP spares requirements levels, a relation must be determined between failures of spare parts, the factors that drive the failures, and the demands which are generated. This chapter introduces the issue of reparable spares forecasting and is divided into the following sections: Background and Important Research Aspects. The background section provides a discussion of issues important to spares demand forecasting. Initially, the indentured component structure of aircraft spares and the difference between consumable and reparable spares will be presented. Following the initial discussion of component structure and spares categorization, the current Air Force systems used to estimate reparable and MRSP spares demand, the Recoverable Consumption Item Requirements System (D041) and the Requirements/Execution Availability Logistics Module (REALM), will be reviewed. To conclude the background section, recent research conducted by Headquarters United States Air Force (HQ USAF/LGSI) and the Logistics Management Institute (LMI) will be presented to exhibit a potential problem with D041 and REALM, which both currently use only flying hours to compute/forecast reparable and MRSP spares quantities.

The section on important research aspects will cover significant areas of this demand forecasting research study. In this section, the problem statement, research objectives, research questions, methodology, assumptions, scope, limitations, and implications will be briefly discussed. To conclude the chapter, an overall research summary will be presented.

Background

Reparable spares demand forecasting is a difficult and involved process. However, the indentured structure of aircraft components and the categorization of spares, into consumables and reparables, allow for line item tracking of specific aircraft failures and demands, which are later used to compute spares requirements levels.

Indentured Component Structure. As Isaacson explains, "Aircraft are assumed to have an indentured component structure: they are composed of line replaceable units (LRUs) that are composed of shop replaceable units (SRUs) that are composed of what are called sub SRUs" (Isaacson, 1988:4). When an aircraft experiences a failure of an LRU or SRU component spare, the failure normally results in a demand on base supply. Therefore, base supply could more accurately stock reparable LRU and SRU spares if these failures could be determined with a greater degree of certainty. However, the failures of reparable aircraft spares are uncertain and erratic, resulting in a difficult demand forecasting process. The indentured LRU and SRU components of an aircraft are also further categorized as either consumables or reparables.

Consumables and Reparables. Consumables and reparables are defined as:

> Consumables are those items which are expended, consumed or used up beyond recovery in the process of the use for which they were designed or intended ..... Reparables are defined as those items that may be repaired or reconditioned and returned to a serviceable condition for reuse. (Christensen, 1985:1)

Reparable LRUs, and certain SRUs, are reconditioned or repaired in the field through a process known as the base level repair cycle system (Christensen, 1985:2). The base level repair cycle is the first echelon of a two echelon system known as the Aircraft Logistics Support Network. The echelon above base level repair is known as the depot level (Isaacson, 1988:6). The Air Force Logistics Support Network is depicted in Figure 1-1 on the next page. Depending on a particular base's percentage of base repair, and an LRUs or SRUs expendability, recoverability, repairability category (ERRC) code and technical order specifications, the LRU or SRU can be repaired at the base or at the depot level (Christensen, 1985:1).

LRUs and SRUs that can be repaired are referred to as reparables or repair cycle assets. Reparables are typically complex, expensive, and have low demand rates (Sherbrooke, 1992:45). "Ninety-five percent of all money spent on supplies stocked in a

typical base supply organization is spent on repair cycle assets" (Christensen, 1985:2). However, in spite of this large investment, "Reparable assets consist of only five percent

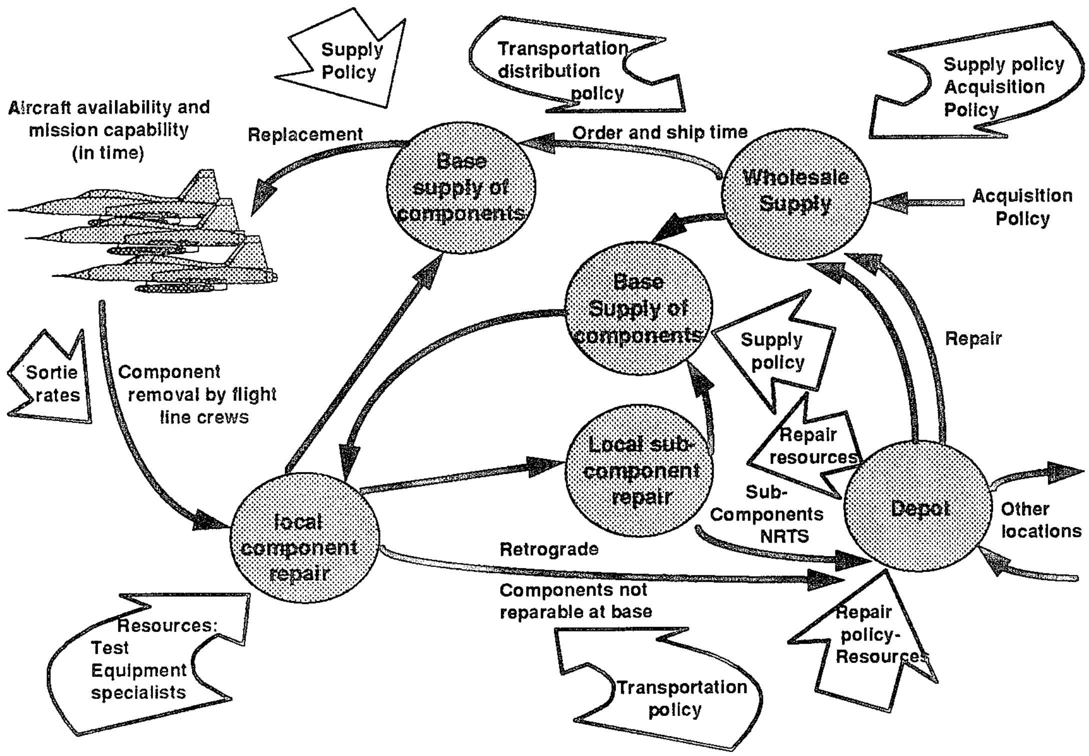

Figure 1-1. Aircraft Logistics Support Network (Isaacson, 1988:6)

of the total line items in the Air Force inventory because of their high cost and repairability" (Christensen, 1985:2).

Reparables become extremely important in supporting Air Force weapon systems, especially in a wartime environment. The Air Force also gains an economic advantage by procuring only the required number of reparables, due to the large investment required to build-up home station and MRSP inventories. However, forecasting demand for aircraft reparable spare parts is a difficult task. This difficulty arises from: "(a) substantial variability in spares demands, even in peacetime (statistical uncertainty), and (b) instability

in force structure, force beddown, flying hour programs, funding profiles, item reliabilities, and other characteristics (state-of-the-world uncertainty)" (Adams, 1993:1).

This statistical and state-of-the-world uncertainty appear to produce offsetting effects on demand forecasting. The DoD, particularly the Air Force, has sponsored significant research to reduce the statistical uncertainty and variability in demand forecasting. However, the current downsizing of the DoD, representative of state-of-the-world uncertainty, contributes to the demand forecasting uncertainty. Another aspect of the inherent demand forecasting uncertainty is possibly found in the current D041 system of the Air Force Materiel Command (AFMC).

D041. The D041 system computes requirements for aircraft reparable spares and uses an eight-quarter moving average to estimate demand for assets, which, as Adams explains, is "A technique that gives no more weight to recent observations than to older, less relevant observations" (Adams, 1993:1). D041 also assumes flying hours and the number of demands are proportional and follow a linear relationship (Adams, 1993:2). In other words, the more a weapon system is flown, the demand for spares should increase at a proportional rate. By assuming demands are only related to flying hours, D041 provides adequate estimates for those reparable spares which actually fail on a flying hour basis. However, D041 could over or under stock those items which fail according to weapon system operational characteristics other than flying hours. In comparison to D041, REALM is another flying hour based forecasting system, which focuses on computing MRSP spares estimates.

REALM. According to Abell, "REALM is the software module of AFMC's Weapon System Management Information System (WSMIS) that computes requirements for war readiness spares" (Abell, 1993:xxx). However, REALM also assumes demands are related to only flying hours and computes requirements for only flying hour driven parts (Clarkson, 1994:4).

Initial problems with REALM requirements computations were highlighted in the Coronet Warrior exercise conducted in 1988. During this exercise, the 94 Tactical Fighter Squadron from Langley AFB, was supported by a remove/repair/replace (RRR) War Readiness Spares Kit (WRSK) assessed at C-2 for sorties. However, despite this tailored down kit, the demands for spare parts were less than expected; only approximately 35 percent of the assets in the kit were issued during the exercise (Pipp, 1988:1). Coronet Warrior lead to the conclusion that "Demand/break rate data bases need major review, especially in regard to non-optimized and wartime adjustment factor items" (Pipp, 1988:3). As depicted in Coronet Warrior, the WSMIS/REALM calculation of the number of required reparable spares, based purely on flying hours, proved to be inaccurate. Nevertheless, Coronet Warrior was considered a single data point to be used as a benchmark in further investigation of reparable demand forecasting.

To summarize Air Force spares demand forecasting, Air Force aircraft have an indentured component structure and are comprised of both consumable and reparable spares. The demand for reparable spares is normally low, erratic, and uncertain in nature, which presents difficulty in accurately forecasting demand. The primary reparable and MRSP spares demand forecasting programs, D041 and REALM, assume demands are driven solely on a flying hour basis. However, recent research by HQ USAF and the LMI indicates the linear relationship between demands and flying hours is questionable.

Recent Research. In a 1994 research study conducted by HQ USAF/LGSI and the LMI, an analysis of Operation DESERT SHIELD/STORM data reflected the strictly flying hour based approach for estimating spares demand is not totally accurate (HQ USAF and LMI, 1994:6). As shown in Figure 1-2 on the next page, HQ USAF/LGSI and the LMI determined that assuming demands are proportional to flying hours tends to overstate demands. If an assumption is made demands are purely sortie based, demands would be understated. The "truth," or the actual number of demands/sortie, lies between

flying hours and sorties. Thus, individual parts may be sortie driven, flying hour driven, or a combination of the two (HQ USAF and LMI, 1994:6).

The uncertainty in the relationship between demands, flying hours, and sorties is the impetus behind this research. This research covers new territory in demand

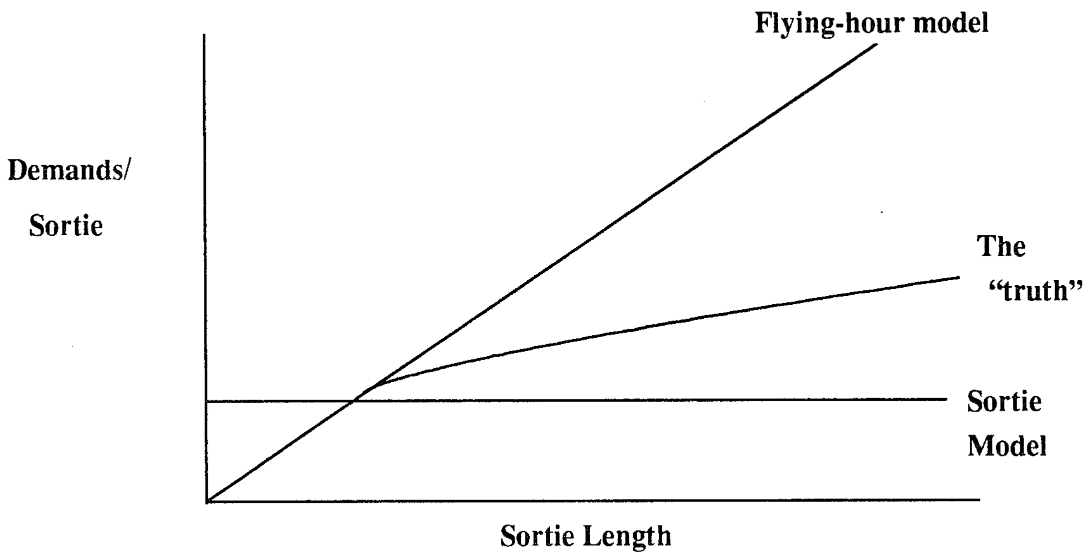

Figure 1-2. Graph of Demands/Sortie versus Sortie Length (HQ USAF and LMI, 1994:6)

forecasting because it analyzes the relationship between reparable demands, flying hours, and sorties at the work unit code level. The research goal is to develop a flying hour, sortie, demand relationship at the work unit code level, which can be used to develop more accurate, reliable MRSP configurations. The important aspects of the research study will now be covered in the next section.

Important Research Aspects

To provide an overview to this research study, a brief synopsis of the following research aspects will be provided: problem statement, research questions, methodology, scope, limitations, assumptions, and implications.

Problem Statement. The specific problem is to determine whether demands/ maintenance actions of aircraft reparable spare parts are correlated, at the work unit code level, to flying hours and/or number of sorties. Current requirements models assume a direct, linear relationship to the number of flying hours. However, demands/maintenance actions could be driven by other factors, or a combination of factors, such as flying hours and/or number of sorties.

Research Objectives. The overall objective of this research is to expand on previous demand forecasting research and focus on a different aspect of demand forecasting. This aspect is a "pioneering" attempt to align demands, flying hours, and sorties at the work unit code level. The study has two research objectives. The first objective is to determine if demands/maintenance actions, flying hours, and number of sorties are correlated at the work unit code level. Based on extent of correlation from the first objective, the second objective is to identify specific work unit code decision rules which estimate the demands, or maintenance actions, given a specified quantity of flying hours and/or number of sorties. If correlation exists between demands/maintenance actions, flying hours, and number of sorties at the work unit code level, it could possibly be used as a more accurate means of forecasting reparable spare parts demand used in the computation of Air Force peacetime and wartime/MRSP requirements levels.

For the purposes of this study, the work unit code level is defined in the following manner. A typical work unit code is five alpha-numeric digits, for example, 11A99. 11A99 is considered the "five-digit" work unit code level. The two, three, and four work unit code levels correspond to the number of the same digits in any similar group of work unit codes. For example, 11A9_ is the "four digit" work unit code level, while 11A _ _ is the "three digit" level. The "two digit" work unit code level is considered 11 _ _ _. The blank spaces represent any other alpha-numeric digits. For analysis purposes, the work unit codes are aggregated into two, three, four, or five digit levels by matching the same

first two, three, four, or five digits of the work unit codes. A breakdown of the work unit code structure and a comparison of the two digit work unit codes to respective weapon system components is included in Appendix A. The study targets specific work unit code levels because Air Force maintenance organizations track all maintenance actions performed on a weapon system through the use of the five digit work unit codes.

Research at the work unit code level is important for the following reason: If the number of specific work unit code level maintenance actions can be correlated to flying hours and/or sorties, a match of the work unit code to its corresponding national stock number could provide forecasts of the number of spares required for a specified flying hour and sortie profile. Furthermore, if a specified wartime mission profile is known, the work unit code level/national stock number match could be used to determine the required spares configuration needed in any deployable MRSPs. Another significant factor for focusing the research at the work unit code level is that the data used in this research tracks maintenance actions on the aircraft, not demands on base supply. In reality, each maintenance action on the aircraft may or may not result in a demand on supply. However, to simplify the study, spares demand and maintenance actions are assumed to be equivalent.

Research Questions. The following research questions are developed for this research study:

1. Is there a relationship between demands/maintenance actions, flying hours, and number of sorties at the work unit code level?

2. Can decision rules be established to forecast demands/maintenance actions based on a spares work unit code alone?

These research questions will tested and answered by evaluating the extent of correlation between demands/maintenance actions, flying hours, and number of sorties at the work unit code level. The analytical techniques of multiple regression, Poisson

regression, and fitting of a Poisson process will be used to evaluate the data and are outlined in the following section covering methodology.

Methodology. D041 and REALM currently assume a direct linear relationship between spares demand and flying hours (Clarkson, 1994:4). This research methodology will use a three phase approach to determine the extent of correlation between the criterion variable, demands/maintenance actions, and the predictor variables, cumulative flying hours and number of sorties. Phase One uses multiple regression. Phase Two focuses on Poisson regression, while Phase Three evaluates the demands/maintenance actions, flying hours, and sortie relationship by fitting a Poisson process. Each phase of the methodology will now be presented.

Multiple Regression. The objective of multiple regression is to construct a probabilistic model that relates a dependent, or criterion variable, Y, to more than one independent or predictor variable (Devore, 1991:526). The criterion variable used for the multiple regression is demands or maintenance actions. The predictor variables are cumulative flying hours and number of sorties. Upon obtaining the criterion and predictor variables from the data, multiple linear regression will be performed to determine whether or not maintenance actions, cumulative flying hours, and number of sorties are correlated.

Multiple regression will be performed against "reduced," first-order models and "full," second-order, interaction models. Specific hypotheses will be developed to evaluate the multiple regression models. The hypotheses to be tested for the reduced model are:

$$H_o : \beta_1 = \beta_2 = \ldots . \beta_k = 0$$

$$H_a : \text{at least one } \beta_i \neq 0 \ (i = 1, \ldots\ldots, k)$$

Variables with p-values greater than $\alpha = 0.05$ will be considered as non-contributing factors in any reduced multiple regression models.

Additional multiple regression analysis will be attempted to introduce second order and interaction terms to the multiple regression model. The "reduced" first order multiple regression model and a "full" multiple regression model, which contains all higher order or interaction variables, will be tested to determine if additional terms contribute to the models. The hypotheses to be tested are:

H_o : model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$ (reduced model)

H_a : model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$ (full model)

If H_a is true, p-value comparisons to an $\alpha = 0.05$ will be performed to determine which higher order or interaction terms contribute to the model. Upon completing the multiple regression analysis, Phase Two of the methodology, Poisson regression, will be used to analyze the data.

Poisson Regression. Poisson regression is based on the discrete Poisson distribution and is normally used to evaluate count data. The data used in this study represents discrete counts of maintenance actions occurring at specific work unit code levels for a specified number of flying hours and sorties. The Poisson distribution is suitable for this analysis because the number of demands/maintenance actions changes and is dependent on the level of flying hours and sorties experienced by each individual aircraft.

Three Poisson regressions will be performed against specific work unit code levels. Initially, two Poisson regressions will be run, one for cumulative flying hours and one for number of sorties. The third Poisson regression will include both cumulative flying hours and number of sorties. The primary measure of fit in Poisson regression is the deviance, which is similar to the residual error in linear regression. Generally, the smaller the value of the deviance, the better the fit of the model (Statistix, 1985:183). The model with the smallest deviance will be used to estimate demands or maintenance actions from a validation data set. Comparison testing of p-values to an $\alpha = 0.05$ will determine which

variable coefficients actually contribute to the resulting Poisson regression model. Upon completing Poisson regression, the data will be analyzed as a Poisson process in Phase Three of the methodology.

Poisson Process. Fitting a Poisson process is similar to Poisson regression in that both techniques are based upon the discrete Poisson distribution. The random variable of interest represents the total number of X occurrences of some phenomenon during a specified period of time or within a specified region. If the physical process generating the occurrences satisfies three conditions, (stationary, independent time increments, and the probability of two or more occurrences in time *t* is some function of *t*), then the distribution of X must be a Poisson distribution (Degroot, 1986:254,255). For this study, the Poisson process is fit to the data to model the number of demands or maintenance actions that occur over a specified number of flying hours or sorties.

In analyzing the data by fitting a Poisson process, parameters will be estimated from a 1993 data set. These parameters will be used to calculate the expected number of maintenance actions from a 1994 validation data set. Confidence intervals and probabilities of falling outside the bounds of the confidence intervals will also be calculated. Residuals on the Poisson process will be determined by subtracting the expected number of 1994 maintenance actions from the actual number of 1994 maintenance actions. Also, a null hypothesis that the 1993 and 1994 demand rates are the same will be tested against the alternate hypothesis that the demand rates are different for each two digit work unit code level.

The three phase research methodology uses multiple regression, Poisson regression, and fitting of a Poisson process. Initial analysis with multiple regression provided limited results. After meetings with the AFIT Statistics Department and a review of the data structure, Poisson regression and fitting of a Poisson process were attempted to improve upon the limited results obtained through multiple regression. The

methodology was eventually segmented into the three phases in an attempt to find the optimal method of aligning demands, flying hours, and sorties at the work unit code level. The following section covers the assumptions of the research.

<u>Assumptions</u>. The assumptions made in performing this study are outlined as follows: First, the demands/maintenance actions which are generated are assumed to be steady state and all aircraft are assumed to be configured in the same manner. This assumption is necessary because different types of sorties suggest different requirements be placed on the aircraft. For example, an air-to-air sortie requires different "demands" of the aircraft, as compared to an electronic counter measure sortie. Second, a determination cannot be made from the data as to which aircraft flew what type of sortie. It is assumed any one sortie flown is similar to any other sortie. Finally, every sortie that contains a work unit code is assumed to result in a demand on supply or a maintenance action on the aircraft. In other words, demands and maintenance actions are assumed to be equivalent. However, in reality, a certain percentage of malfunctions on an aircraft would result in "cannot duplicate" or "bench check serviceable" actions by maintenance personnel, which do not generate actual spares demands against base supply.

<u>Scope</u>. The scope of the study outlines the extent and outlook of the research. The extent of the research is focused on one weapon system and its reparable spares failures, in order to determine any relationship between demands/maintenance actions, cumulative flying hours, and number of sorties. The weapon system of interest in this study is the F-15C. If a relationship can be identified for one specific MDS, similar techniques may be applied to other types of aircraft. However, because the F-15C is a fighter aircraft, the results may be skewed positively or negatively from other types of non-fighter aircraft. For example, the same electronics equipment may be found on an F-15 and a C-141 transport plane. The fighter aircraft may experience significantly more stress because of increases in G-forces or rapid increases/decreases in acceleration. Due

to these factors, a reparable item, such as electronics equipment, on a fighter may fail at an earlier rate than that of a C-141. Also, transport aircraft typically have longer sortie profiles than fighters, thus there could be more or less reparable failures on a transport as compared to a fighter, depending on the specific component. Simply said, the type of mission performed by different weapons systems may be a large factor in generating demands/maintenance actions and this will not be analyzed. However, since all aircraft inevitably break, the methodology could possibly be used to derive failure rate demand patterns for other types of aircraft.

The outlook of the study is focused on a specific time period and uses Reliability and Maintainability Information System (REMIS) data. The data bases used in this study are from a discrete timeframe covering less than a year, thus, the study in a time sense is narrow. This narrow timeframe does increase the possibility of abnormal demand figures. The data is worldwide F-15C data and covers only peacetime flying profiles. The results would undoubtedly be different, to some extent, if the data were from a wartime or even an exercise environment. Also, only REMIS data will be evaluated in this study. Due to the downloads of Consolidated Aircraft Maintenance System (CAMS) data into REMIS, the REMIS database was considered the best source to obtain demand/maintenance action, flying hour, and sortie information on an operational weapon system.

Limitations. Limitations are the extreme points or boundaries which restrict or confine the research. Several of the limitations include: lack of diversity in the type of aircraft studied, timeline of the study, constraining factors within the data, environmental inputs, and the quality of maintenance performed on each aircraft. The study is limited to only one type of aircraft in order to simplify assumptions used in the methodology. The timeline of the study is limited to discrete periods based on the data downloaded from REMIS. The 1993 database covered eight months of data, while the 1994 database

contained only five months of data. Larger data sets covering longer timeframes could improve overall analysis employed in the methodology.

A major limitation to this study is the data. Initial sorting of the data files indicated numerous work unit codes with only a small number of occurrences. However, this is typical for low demand, reparable items. Due to this small number of occurrences, the number of regressions performed against specific, individual work unit codes will be limited, especially at the five digit work unit code level. A solution to the limited number of occurrences is to aggregate the work unit codes at the two, three, or four digit level and perform the regression/estimation analysis at the various work unit code levels.

Also, 160 of the aircraft were deleted from the 1993 data set due to an absence of maintenance action data, leaving a population of 247 aircraft. However, the 1994 data set contained data on 340 aircraft, but for only a five month period. Despite deleting 160 aircraft from the 1993 data and the limited timeframe covered by the 1994 data, both data sets are still quite large. Each data set contains nearly 50,000 combined sortie and maintenance action images, which provides a large sample suitable for analysis.

A final limitation with the data is the number of available predictor variables. The predictor variables used in the multiple and Poisson regression analysis were cumulative flying hours and number of sorties. However, in analyzing "reduced" versus "full" regression models, additional carriers can be added by taking these predictor variables to a power, or linearly combining the variables, and inserting them in the model. Based on the REMIS data used in this study, only flying hour and sortie data could be obtained. The availability of additional predictor variables, such as engine cycles or "logged" times when a specific component is in use, for example, electronic countermeasure components, could improve the correlation present within the regression models.

Environmental factors are also a limitation to the study. Factors such as heat, humidity, and sand, will not be considered, however, these variables are possibly a

contributing factor to demands or maintenance actions. Finally, the quality of maintenance performed is also vital to a spares performance. Past histories of each airframe play key roles in future failure rates of reparables. Despite this fact, the age and accumulated flying hours on each airframe will not be analyzed.

All of the previously discussed factors are limitations of this study. After identifying these limitations, demands or maintenance actions for specific reparables can be identified by the tangible variables contained in this report. The limited variables play a more minor role.

Implications. From this research, a better model for estimating demands or maintenance actions for reparables could be developed, thus potentially saving the Air Force tight budget dollars. Initial estimates by HQ USAF/LGSI and LMI predict substantial savings by estimating demand from both flying hours and sorties. Based on the 1986 USAF War and Mobilization Plan (WMP-5), an F-15 C/D 30-day MRSP costs approximately $14.7 million. Under the HQ USAF/LGSI and LMI combined flying hour and sortie approach, cost of a similar MRSP, based on the 1993 WMP-5, drops to $7.2 million (HQ USAF/LGSI and LMI, 1994:9). Therefore, this research has the potential to significantly reduce the spares requirement for Air Force budget dollars.

Air Force logisticians can also make better decisions by having better failure predictors. By obtaining accurate knowledge of failure characteristics of spares, a logistician can use the most appropriate demand forecasting techniques to stock required quantities of critical items, which ultimately enhances operational readiness. Another implication of this research is to design more efficient and effective MRSP configurations, allowing for more combat capability per dollar. Having the right number of parts going to the right place at the right time, not only saves money, but also conserves vital mobility airlift capability. Other implications include: more accurate capability assessments, better

predictions of failures to demands, and more accurate allocations of scarce resources in a downsizing military environment.

Summary

The problem of forecasting failures of reparable aircraft spares is filled with uncertainty. This uncertainty complicates the issue of determining accurate reparable spares levels. Given the time-tested problem of forecasting demand for reparable spare parts, an improved method is needed to determine what drives specific parts to fail, when these parts will fail, and how many need to be ordered. The current D041 and REALM computation processes, which are based on the linear relationship of demands to flying hours, are being closely scrutinized by HQ USAF and the LMI.

HQ USAF and the LMI have studied the effects of incorporating both flying hours and sorties as predictors of failures and demand. However, this research was aggregated across entire weapon systems. The distinction of this research is to target demands/ maintenance actions at the specific work unit code level and determine if a relationship exists between demands/maintenance actions, cumulative flying hours, and number of sorties. Capability to properly identify demand rates for specific spares, or groups of spares, becomes a key objective in forecasting reparable spares. The system can be improved upon and the bottom line of this research is to seek out a better method.

The remainder of this research focuses on aligning demand/maintenance actions for spares with flying hours, and sorties, at specific work unit code levels. Chapter II provides a literature review covering historical research on forecasting demands for spares, current models used to calculate spares requirements, and a discussion on how MRSPs are authorized, built, and maintained. Chapter III outlines the methodology and covers the origin and make-up of the data. Chapter IV presents and analyzes the results

obtained from applying the research methodology. Finally, Chapter V presents the conclusions of the research and suggests recommended areas of follow-on research.

II. Literature Review

Introduction

The purpose of this literature review is to examine historical research completed on determining accurate demands for aircraft spares and how these demand forecasts affect MRSP spares levels or requirements. The research covered in this literature review includes only past research examining the relationship between reparable failures and/or predictor variables, which is the focus of this study. Demand research focusing on other analysis methods, such as time series analysis, will not be reviewed.

The chapter will review the historical demand forecasting research and examine the models used to calculate reparable spares demands. A review of reparable spare parts management in the civilian sector will also be presented. Following the civilian sector review, lessons learned from past exercises, such as Coronet Warrior and Bull Rider, will be reviewed to highlight the necessity for further research in ascertaining whether all spares demands are purely flying hour driven or are somehow affected by other operational characteristics of the weapon system. The chapter will conclude with a discussion of how demand forecasting affects MRSPs and how MRSPs are currently authorized, built, and maintained.

Historical Review

RAND Research. Forecasting demands for aircraft recoverable spare parts has challenged researchers for decades. Beginning in the 1950s, RAND Corporation began pursuing the problem of forecasting demands for aircraft recoverable spare parts. One of the earliest works on aligning spares demands with their underlying failure modes was conducted by Geisler, Brown and Hixon of the RAND Corporation in July 1954 (Adams, 1993:4). This research effort targeted three B-47 bases and compiled over 1300 aircraft

months of data, which included both consumables and recoverables (Geisler, 1954:ii). After several months of research and data analysis, the researchers concluded:

> It is shown that there is a surprisingly low amount of demand both as to kind and quantity of aircraft spare items,.... Furthermore, we could find no significant correlation between the kinds or quantity of items demanded and the aircraft flying activity, measured in flying hours, landings or aircraft months. (Geisler, 1954: ii)

Following this initial research, Geisler and Brown published a report concerning the lack of significant correlation between the number of demands and flying activity. In this report, Geisler and Brown concluded:

> ... the daily combined demand over all items show more variation than expected from the Poisson distribution ... if the Poisson distribution is used to represent the demand pattern for spare items because of its mathematical convenience, the actual distribution for either individual items or combined may be more extreme, in that the variance of the distribution will be greater than the mean value of demand. (Brown, 1954:ii,iii)

From this initial research, it was recognized very early that accurate prediction of demand for aircraft spares is an extremely complicated process and not easy to determine.

The Poisson distribution, which is discussed by Geisler and Brown, "is the most widely known and often used form of stochastic model with important mathematical properties that make it especially tractable and useful" (Abell, 1993:xxx). If the time separating demands for aircraft spares follows an exponential distribution, the quantity of spares demanded during a specified period of time is said to be Poisson distributed (Sherbrooke, 1992:21). The probability that a specific event x occurs under the Poisson distribution is represented by:

$$p(x|\lambda\tau) = \frac{(\lambda\tau)^x e^{-\lambda\tau}}{x!}$$

where e = base of the natural logarithm system and has numerical value of approximately 2.71828

τ = mean resupply time

λ = mean rate of demand

x = number of units in resupply (Feeney, 1966:393).

The event "x" can be thought of as a failure of a spare that ultimately results in a demand. For the Poisson distribution, the variance of X, Var[X], where X is a random variable, is equal to the expected value of X, E[X]. Therefore, the variance to mean ratio, [VTMR], is equal to one (Sherbrooke, 1992:21). However, the majority of processes modeled by a Poisson distribution show some variability and are referred to as compound Poisson distributions. As Christensen explains, "The main feature of the compound Poisson distribution is that the variance can exceed the mean" (Christensen, 1985:7). Although the compound Poisson is theoretically more accurate, the simple Poisson is assumed to provide reasonable answers due to the difficulty in calculating variances of individual items (Mitchell, 1983:445).

Following Geisler and Brown's research, which concluded demand for aircraft spares did not follow a Poisson distribution, Youngs, Geisler and Mirkovich of RAND performed a study focusing on the method of confidence intervals as applied to the Poisson distribution. In this study, the researchers determined, "Since the true demand rate for a supply item is seldom known, it is necessary to estimate it from statistical demand data. This means that the Poisson parameter can at best be estimated subject to sampling error, i.e., it can only be trapped within certain intervals with a specified probability" (Youngs, 1954:1).

Realizing historical demands may not be indicative of true demand predictions, the research by Youngs, Geisler and Mirkovich was the initial study which lead the movement away from the Poisson distribution to the negative binomial distribution, as a means of modeling demand for aircraft spares (Adams, 1993:7). The negative binomial distribution generalizes the Poisson distribution and, as Adams explains, "The negative binomial distribution applies to situations in which events occur at random, but the variance of the number of events in nonoverlapping time intervals of equal length is higher than allowed

by the Poisson distribution" (Adams, 1993:xxi). Over short time intervals, the variance to mean ratio of demand may not change to a great extent. However, "Over longer time periods, the variance to mean ratio of demand changes, sometimes substantially, and is greater than one" (Sherbrooke, 1992:58). To compensate for this demand uncertainty, the negative binomial distribution uses both the mean and variance of demand and recognizes variance to mean ratios greater than one (Sherbrooke, 1992:58). The negative binomial distribution is represented as follows:

$$neg(x) = \binom{a+x-1}{x} b^x (1-b)^a$$

where

$a = \mu \ / (\text{V-1}),\ a > 0$
$b = (\text{V-1}) / \text{V},\ 0 < b < 1$
μ = mean
V = variance to mean ratio, V > 1 (Sherbrooke, 1992:60-61).

In 1956, Bernice Brown, also from RAND, used the prior RAND demand research from 1954 and 1955 to publish a formal research memorandum exploring the demand characteristics of aircraft spares (Adams, 1993:8). In this memorandum, Brown realized the majority of prior research was only performed on a single aircraft, the B-47, and much work remained to be accomplished in the area of demand forecasting (Brown, 1956:iii). Nevertheless, Brown concluded:

> Low average demand rates are characteristic of a large proportion of all aircraft parts. The slow moving, low cost parts account for a small fraction of the total dollar value of issues, but because of their large number and, often their essentiality to the functioning of the aircraft, they constitute a significant logistics problem. .... Demand for most spare parts tends to be erratic. (Brown, 1956:vii)

To account for this low demand of a large proportion of aircraft spares, T. A. Goldman of RAND performed research in 1957, which made the first suggestion of possibly looking at spares in aggregate groups instead of single line items (Adams,

1993:13). Goldman's research concluded: "The family of parts rather than the individual part number should be the basic unit in demand analysis and forecasting. .... The levels of demand for spares appears to be associated with certain fundamental characteristics of the part" (Goldman, 1957:vi).

In 1963, following Goldman's research, H. S. Campbell of RAND focused on using multiple correlation and regression analysis as a method for predicting demand for aircraft spares (Adams, 1993:16). He used data from the B-52 aircraft in researching spares demands against seven operational variables: "Sorties flown, flying hours, flying hours at low altitude, bombing navigation training units, fire control system usage, ECM system usage, and periodic inspections" (Campbell, 1963:14). Using multiple correlation and regression analysis with net demands as the dependent variable, Campbell found coefficients of multiple determination, R^2, values ranging from a high of 0.74 for electronic systems to a low of 0.20 for fire control and gunnery systems (Campbell, 1963:22,23). After analyzing his results, Campbell concluded: "Demands appeared to be related to flying hours and sorties, with the former providing the stronger relationship. Other operational variables showed little relationship, and multiple correlations of demand on several operational variables typically showed little improvement over flying hours alone" (Campbell, 1963:v,vi). A major difference in Campbell's work as compared to the early research of Geisler, Brown and Hixon was Campbell's research included only recoverable items (Adams, 1993:16).

One of the major themes present throughout the 1950s and mid 1960s research was that low demand drives uncertainty in determining future spares levels (Adams, 1993:9). However, in 1964, Feeney and Sherbrooke of RAND introduced a system oriented, instead of an item oriented, approach to forecasting demand for spare parts. Feeney and Sherbrooke's research centered around a mathematical technique known as Bayesian inference, which attempts to reduce the uncertainty in demand forecasting by

studying the performance of comparable items in a system (Feeney, 1964:vi). Bayesian inference is used to "combine the prior distribution on all items with a Poisson demand process to estimate a posterior distribution for demand of each individual item" (Sherbrooke, 1992:73).

Feeney and Sherbrooke also applied Palm's Theorem into the forecasting of demand for recoverable spares (Adams, 1993:18). As Sherbrooke explains, "Palm's Theorem estimates the steady state probability distribution of the number of units in repair from the probability distribution of the demand process and the mean of the repair time distribution" (Sherbrooke, 1992: 21). Palm's Theorem assumes the following:

1. The demand process for an item is Poisson distributed with an annual mean of lambda, λ.

2. The demand and repair processes are independent of each other.

3. The repair time for each failed unit is independent, identically distributed with a mean of tau years, represented by τ. Also, the distribution is unspecified.

4. Slack service capacity exists. There are always infinite channels.

Given these assumptions, Palm's Theorem generalizes that the number of units in repair at any time is Poisson distributed with mean, $\lambda\tau$ (Crawford, 1981:8). Palm's Theorem is also useful in generalizing the basic reparable pipeline quantity model. The basic reparable pipeline quantity model is represented by:

$$s = RCQ + OSTQ + NCQ + SLQ + K$$

where

s = pipeline stock
RCQ = repair cycle quantity; $DDR\ X\ PBR\ X\ RCT$
$OSTQ$ = order and ship time quantity; $DDR\ X\ (1 - PBR)\ X\ OST$
NCQ = not repairable this station(NRTS)/condemned quantity; $DDR\ X\ (1 - PBR)\ X\ NCT$
SLQ = safety level quantity; $C\left(\sqrt{3X\left(RCQ + OSTQ + NCQ\right)}\right)$
K = constant, .5 if unit cost is greater than \$750, or .9 if unit cost is \$750 or less

C = C factor or number of standard deviations to protect against stockouts
DDR = daily demand rate
PBR = percent of base repair
RCT = repair cycle time
OST = order and ship time
NCQ = NRTS cycle time (Christensen, 1985:4).

Palm's Theorem allows for calculations of the specific number of assets in a reparable pipeline. For example, on a base with 100 percent base repair, PBR = 1, an item that averages 10 demands per year, $\lambda = 10$, and takes 0.3 years to repair, $\tau = 0.3$, the average number of assets in the pipeline is 3; $\lambda\tau = (10)(0.3) = 3$.

Feeney and Sherbrooke's research into Bayesian inference and Palm's Theorem was the final RAND research focusing exclusively on the demand forecasting problem (Adams, 1993:19). What soon followed was the start of a series of models focusing not only on the demand forecasting problem, but also the effects of demand on reparable stockage policy.

The first model to appear was known as the Multi-Echelon Technique for Recoverable Item Control (METRIC) (Adams, 1993:19). Over the next several years, variations of METRIC, known as Mod-METRIC, Vari-METRIC, and Dyna-METRIC, were also developed. A brief summary on each of the METRIC models will now be presented:

METRIC. METRIC was developed by Craig Sherbrooke of RAND Corporation in 1966 and is a method for estimating aircraft spares requirements in a multi-echelon, base-depot inventory system (Adams, 1993:xxi,20). METRIC considers only single indenture items (LRUs) and has a system-wide objective of minimizing expected backorders (Sherbrooke, 1992:47). METRIC attempts to improve overall system-wide performance by optimizing procurement of new assets while also evaluating the effects of redistributing on-hand assets between depot and base levels (Sherbrooke, 1968:3). METRIC estimates spares requirements in consideration of the following assumptions:

1. The decision as to whether a base repairs an item does not depend on the stock levels or the workload.

2. The base is resupplied from the depot, not by lateral resupply from another base.

3. The (S-1,S) inventory policy is appropriate for every item at every echelon.

4. Optimal steady-state stock levels are determined.

5. System-wide objective is minimizing expected backorders.

6. System is conservative. There are no condemnations.

7. Demand data from different bases can be pooled (Sherbrooke, 1992:46-47).

Despite METRIC's system-wide objective of minimizing backorders across reparable LRU spares requirements, there are three critiques of the METRIC model:

1. METRIC doesn't consider the LRU/SRU indenture relationship.

2. METRIC doesn't consider end item availability, which is important if cannibalization is allowed.

3. METRIC's minimization of backorders tends to drive the purchase of too many low cost items.

Despite these critiques, METRIC has the distinction of being the first practical application of multi-echelon inventory theory in the Air Force (Sherbrooke, 1986:311).

Mod-METRIC. Mod-METRIC extended the METRIC model by considering the indentured or hierarchical LRU/SRU parts structure of weapons systems (Muckstadt, 1973:474). All of the assumptions previously outlined for the METRIC model also apply to Mod-METRIC. However, there are additional assumptions specific to Mod-METRIC:

1. LRUs are expensive and degrade the mission when they fail. Thus, the percentage of base repair (PBR) should be close to one.

2. SRUs are relatively inexpensive and are remove/replace. There is some PBR for SRUs, but it is more economical to have extra stock of SRUs and fill the depot reparable pipeline with these assets.

3. Every LRU failure is the result of just one SRU failure.

4. SRUs belong to only one LRU (Sherbrooke, 1992:63).

Mod-METRIC's main objective is to minimize LRU backorders, while subject to a cost constraint on both LRU's and SRU's (Muckstadt, 1973:481). Mod-METRIC's original Air Force use was to compute reparable spares requirements on the F-15 weapon system (Muckstadt, 1973:481).

Vari-METRIC. Vari-METRIC was developed by Mike Slay of the Logistics Management Institute (LMI) in 1980 (Sherbrooke, 1986:311). Vari-METRIC was designed to correct inaccuracies in the original METRIC model. When METRIC was first developed, it was clear that the model clearly understated backorders. However, in most instances the errors were not large and the simplicity of the METRIC model overshadowed any inaccuracies (Sherbrooke, 1986:311). Vari-METRIC attempts to improve upon the METRIC model by incorporating the negative binomial approach in estimating expected backorders. By incorporating the negative binomial approach, Vari-METRIC uses both the mean and the variance to compute the number of units in resupply (Sherbrooke, 1992:97,98). Vari-METRIC assumes the following:

1. It is appropriate to use the (S-1,S) inventory policy at each echelon.

2. Repair capacity and parts are ample. Repair time is independent of the number of units already in repair.

3. Poisson demand with a mean that is constant, independent of the number of units in repair or resupply. Pipeline quantities have a negative binomial distribution.

4. No units are condemned.

5. No lateral support. All resupply comes from the depot (Sherbrooke, 1986:311).

Vari-METRIC improves upon METRIC and Mod-METRIC in computing spares requirements, but it is not used extensively in the Air Force. Vari-METRIC is a complex model requiring a significant amount of data and most spares requirements computations produce fairly close results by using the METRIC model.

Dyna-METRIC. Dyna-METRIC was originally developed by R. J. Hillestad of RAND in 1980 (Adams, 1993:21). Dyna-METRIC (Version 4) is an analytic model that uses mathematical equations to forecast how logistics support processes would effect a flying unit's capability in a dynamic wartime environment (Isaacson, 1993:1). All METRIC models prior to Dyna-METRIC considered only steady state conditions, for example, the relatively stable flying activity which is normally experienced in peacetime flying profiles. Dyna-METRIC primarily focuses on the dynamic, flying hour environment, representative of wartime scenarios, and attempts to model spares requirements based on the uncertainty of demands generated during wartime flying activity (Sherbrooke, 1992:184).

Dyna-METRIC has evolved through several enhancements and numerous versions of the model have been developed (Isaacson, 1993:1). Enhanced versions of Dyna-METRIC can generate two different assessment reports. The first report determines performance measures such as spares and aircraft availability. The second report, the problem LRUs report, assesses requirements and identifies a list of problem parts whose support resources and processes constrain aircraft availability (Isaacson, 1993:12-15).

To effectively model the dynamic wartime environment, Dyna-METRIC (Version 4.6) incorporates the following assumptions:

1. LRU demands are proportional to either flying hours or sortie rate.

2. Demands arrive randomly, with a known mean and variance according to either a Poisson or negative binomial distribution.

3. Demands and service process times are independent.

4. Repair and transportation times have known probability distributions (exponential or deterministic mean).

5. There is unconstrained repair capability and no lateral resupply.

6. All aircraft deployed to a single base are identical.

7. Pipeline segments are additive.

8. Aircraft performance measures are computed after attrition.

9. Under the full cannibalization policy, holes are instantly consolidated on as few aircraft as possible.

10. Ability to cannibalize is all or nothing.

11. Repair times vary by component, while transportation times vary by base.

Overall, Dyna-METRIC provides capability assessments by assessing the effects of wartime dynamics while projecting operational performance measures and identifying potential problems (Isaacson, 1993:1). Table 2-1 on the next page summarizes the four METRIC models.

RAND has definitely lead the way in forecasting demand for aircraft reparable spares within the Air Force. Despite the uncertainty and inherent problems in forecasting demand of reparable spares, current Air Force systems perform reasonably well in providing the best available support to the myriad of weapon systems. To provide a contrasting view to Air Force management of reparable spares, management of reparable parts in the civilian sector will now be presented.

Reparable Parts Management in the Civilian Sector. The commercial airline industry encounters problems very similar to those found in the Department of Defense

for estimating demand for reparable (rotable) aircraft parts. American Airlines Decision Technologies Division developed a PC-based decision support system called the Rotable Allocation and Planning Systems (RAPS) to provide forecasts of rotable parts demand.

Table 2-1. Summary of METRIC Models

MODEL	METRIC	MOD-METRIC	VARI-METRIC	DYNA-METRIC
Indenture	Single	Multiple	Multiple	Multiple
Echelons	Multiple	Multiple	Multiple	Multiple
Number of Items	Multiple	Multiple	Multiple	Multiple
Location	Multiple	Multiple	Multiple	Multiple
Demand Assumptions	Steady state, independent, and stochastic demand (Poisson)	Steady state, independent, and stochastic demand (Poisson)	VTMR > 1, independent, stochastic, Poisson demand. Pipeline quantities have negative binomial distribution	Dynamic instead of steady state. Stochastic, multi-period. Considers time dependent scenarios.
Objective	Minimize expected backorders	Minimize LRU backorders	Maximize aircraft availability	Readiness, sustainability, and sortie generation

RAPS provided a multi-million dollar benefit for American Airlines, upon initial implementation, through the identification of over and under allocated parts (Tedone, 1989:62).

RAPS uses linear regression to establish relationships between monthly part removals and various functions of monthly flying hours. Demand data is kept current through monthly updates from an 18-month rolling horizon of spares removals and flying hour data. Coefficients of determination corresponding to the best regressions are calculated and RAPS analyzes possible forecasts based on flying hours or functions of flying hours. Regressions are evaluated on best fit and statistical significance. The entire process of generating demand forecasts by linear regression is completely automated and demand forecasts are sampled periodically to validate the continued use of the system. As a demand forecasting tool, RAPS incurred no costs due to shortages when demand was spread over a month. However, in a worst case scenario modeling total monthly demand on a single day, shortages did occur for some critical spares.

A major benefit of RAPS is an increase in the number of rotable parts which can be analyzed in a single day. An audit trail is also created to record dates and times of parts analysis. A one time savings of $7 million and a recurring annual savings of $1 million were realized by American Airlines on a fleet of over 400 aircraft. RAPS is now the standard tool for allocating rotables at American Airlines for over 50,000 different types of reparable parts. The impact has been a multi-million dollar improvement in the quantity of on-hand inventory resulting in streamlined generation of spares demand into a more effective, reliable process (Tedone, 1989:68).

RAPS is similar to Air Force demand forecasting systems in that RAPS also uses flying hours to forecast demand. Although RAPS has worked extremely well for American Airlines, the program could prove to be too large to manage in the United States Air Force. American Airlines focuses on managing reparable spares for a fleet of

approximately 400 aircraft. In contrast, the Department of Defense and the United States Air Force support a significantly larger number of aircraft, which are stationed across the globe. Nevertheless, the Air Force continues to strive in improving available demand forecasting systems and exercises/real world scenarios provide unique opportunities to produce valuable lessons learned.

Lessons Learned

Numerous exercises, and even Operation DESERT SHIELD/STORM, have provided an exceptional test bed to determine whether or not the various demand forecasting models, particularly Dyna-METRIC, have accurately forecasted demands. A review of lessons learned from past exercises will now be covered.

Exercises. When Dyna-METRIC was first developed, skepticism existed as to whether or not the model produced accurate results. Several MAJCOM exercises tested and validated the accuracy of the model. Tactical Air Command initiated the testing and validation with the Coronet Warrior exercises (Rhodes, 1988:74). The initial exercise was Coronet Warrior I, which was held at Langley AFB, Virginia in 1987 (Pipp, 1988:1). During Coronet Warrior I, 24 F-15 C/D aircraft were flown for 30 days, at wartime sortie rates, with only a remove/repair/replace WRSK, assessed at C-2 for sorties, for logistical spares support. As a compounding factor, maintenance was limited to an avionics intermediate shop and cannibalization actions (Pipp, 1988:1). Given these input parameters, Dyna-METRIC estimated only 4 aircraft to be FMC at the end of 30 days. The actual number of aircraft FMC after 30 days was 17 (Pipp, 1988:1).

Indeterminate factors impacted the difference between the Dyna-METRIC predictions and the actual results. In general, demands were less than predicted (Page, undated:7). Only approximately 35% of the items in the WRSK were issued during the exercise (Pipp, 1988:1). However, innovative maintenance actions and a “teamwork”

focus, on repairing versus replacing those spares requiring maintenance, definitely influenced the reduced number of supply demands. Another factor influencing the number of demands was that most of the Coronet Warrior sorties were integrated combat turns (ICT). During ICTs, the aircraft is refueled, rearmed and relaunched while never shutting down power to systems and one engine. Because most electrical components, and engines, tend to break from the stress of heating and cooling, there were less spares failures because components were not powered down between sorties (Page, undated:7).

The actual Coronet Warrior results were run through Dyna-METRIC model after the exercise was complete. Dyna-METRIC estimated 16 aircraft FMC at the end of 30 days, which is very close to the actual number of 17 FMC aircraft (Page, undated:8). Given these results, Tactical Air Command concluded:

> The Dyna-METRIC model works well, but further refinement to repair logic may improve the models. Demand/break rate data bases need major review ... more accurate estimates of cannibalization and maintenance times must be included in stockage methodology. This would contribute to the development of better and less expensive WRSK. (Pipp, 1988:3)

The Bull Rider exercise conducted by Strategic Air Command and Volant Cape exercise conducted by Military Airlift Command produced similar results to Coronet Warrior; there were more aircraft FMC and fewer spares demands than predicted by Dyna-METRIC. Overall, using Dyna-METRIC to determine requirements in a dynamic environment works well (Page, undated:12). However, one of Dyna-METRIC's underlying assumptions is that LRU demands are proportional to either flying hours or sortie rate. Failures of some spares in a readiness spares kit may or may not be driven by flying hours, sorties, or a combination of known or unknown operational factors. The uncertainty in determining exact causes of failures is again the thrust of this research. The uncertainty also presents formidable problems in determining exact quantities of assets required in Mobility Readiness Spares Packages (MRSP).

Authorizing, Building, and Maintaining MRSPs

MRSPs are additive stockage levels, above a base's peacetime operating stock, for operational squadrons to support their wartime taskings as outlined in the USAF War and Mobilization Plan (WMP) (Clarkson, 1994:2). Two of Dyna-METRIC's main uses are to determine spares requirements, as well as, a list of problem spares, which become crucial when configuring and building MRSPs.

The process of authorizing, building, maintaining, and ultimately deploying MRSPs is extremely complex. Actions must be accomplished at the field level, the Major Commands, the Air Logistics Centers and Headquarters United States Air Force (HQ USAF)(Clarkson, 1994:2). All MRSPs must first be authorized in the MRSP Authorization Document published by the HQ USAF War and Mobilization and Planning Office (HQ USAF/XOX). An MRSP cannot be built and fielded unless an authorization exists in the MRSP authorization document. The operational requirements, (for example, sorties, utilization rates), plus direct support objectives and operational employment concepts are the major factors which drive the scope and depth of the MRSP (Clarkson, 1994:2). Figure 2-1 on the next page provides a top to bottom diagram of the how an MRSP is authorized.

Once an MRSP is authorized, it enters a lengthy review cycle of approximately one year. The review cycle is designed to ensure the spares package includes all necessary spares to support the scenario for which the package was authorized. The annual review process is comprised of three separate processes: the pre-review, the review, and the post-review (Clarkson, 1994:3). During the pre-review, system program directors suggest additions and deletions to the MRSPs based on the historical usage data and feedback from the major commands (Clarkson, 1994:4). The review process involves analyzing demand data to determine actual spares requirements to include in the MRSP. Sources of

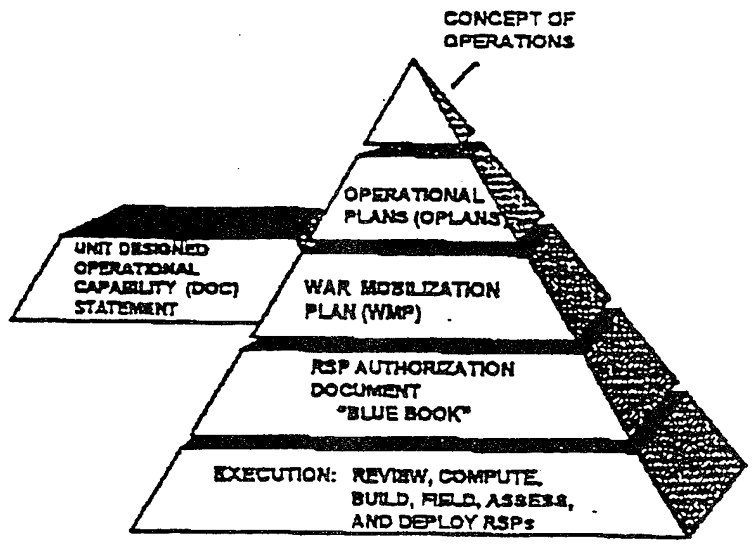

Figure 2-1. How an MRSP is Authorized (Clarkson, 1994:3).

demand data include: D041 rates and factors (which provide worldwide averages on spares usage) and usage data from major command MRSP managers.

After the requirements determination is complete, the Requirements/Execution Availability Logistics Module (REALM) is used to actually compute the MRSP requirements (Clarkson, 1994:4). REALM is the software module of Air Force Materiel Command's Weapon System Management Information System (WSMIS) that computes requirements for war readiness spares (Abell, 1993:xxx). WSMIS uses Dyna-METRIC to assess the wartime capability of existing MRSPs (Blazer, 1988:26). The system used to assess WRSK requirements, prior to Dyna-METRIC, was the WRSK Requirements Computation System (D029). However, in studies performed comparing the requirements cost, backorder performance, and aircraft supportability between the WRSK Requirements Computation System (D029) and Dyna-METRIC, the results revealed Dyna-METRIC computed better, more efficient wartime requirements (Blazer, 1988:26).

Nevertheless, REALM has one main disadvantage. It will only compute requirements for flying hour driven parts. The parts assumed to be non-flying hour driven are known as non-optimized (NOP) items. The NOP requirements are computed external to the guidelines of REALM (Clarkson, 1994:4). The impact of inaccurate forecasts of NOP items can be shown in the make-up of a B-1B, 6 PAA, MRSP. For example, a B-1B, 6 PAA, 14 day MRSP is comprised of 248 line items (669 units) equating to a cost of approximately $69.2 million. Approximately 45 percent (91 line items, 157 units) of the MRSP is made up of NOP items resulting in a cost of $31 million. Because NOP items are expensive and comprise such a large part of this B-1B MRSP, the $31 million price tag suggests a better method is needed to ensure we are putting the right number of NOP items in MRSPs to minimize cost while maximizing aircraft availability (Clarkson, 1994:6).

Prior to the actual REALM computation, the post-review, which is the last of the three MRSP review processes, is conducted. The post review is a final audit check by the system program directors and MAJCOM MRSP managers to further validate established requirements before the REALM computation (Clarkson, 1994:5). Once the post-review is complete, REALM computes the war readiness spares requirements. REALM also uses an embedded model known as the Aircraft Sustainability Model (ASM) to perform a marginal analysis computation to find the most efficient and least cost mix of spares to provide optimum aircraft availability for any given operational support objective (Clarkson, 1994:5).

Normally, during the three step review process, two MRSP kits are built and reviewed. One kit is the contingency kit which supports the force structure and configuration of a squadron for the next fiscal year. The second kit is the buy kit which supports the projected force structure and configuration two years into the future. The

standard time is six months from the annual review to fielding of a new or reviewed MRSP (Clarkson, 1994:3).

The complete process of building MRSPs is extremely expensive to the DoD, not only for the time and manpower invested, but also for the price of the reparable spares. MRSPs are basically comprised of reparable items which are high cost items with low demands. Because the USAF, as a segment of the DoD, spends such a large amount of money on MRSP spares, an economic advantage is gained in procuring only the required number and correct mix of reparable spares. The required number of spares can be more accurately determined if a better method of predicting future spares failures, which ultimately drive demands, can be established.

Currently, REALM, as well as Dyna-METRIC, only focus on flying hour or sortie driven spares failures (Clarkson, 1994:4). Recent research by HQ USAF/LGSI and the LMI in the area of forecasting readiness spares requirements, and lessons learned from past exercises, as well as, Operations DESERT SHIELD/STORM, indicate demand for spares may not be purely flying hour driven (HQ USAF and LMI, 1994:6). Based on this research, REALM and Dyna-METRIC may overstate or understate spares requirements and over or under-allocate available budget dollars on the wrong quantities of readiness spare parts. An accurate method of forecasting spares requirements, based on the most likely failure modes of particular spares, is required. An accurate forecasting method would assist the Air Force in balancing aircraft availability against available budget dollars, when building and configuring MRSPs.

Summary

Forecasting demand for reparable spares is a difficult and involved task. In this literature review, past research performed by RAND Corporation in the area of reparable spares demand forecasting and civilian reparable parts management have been reviewed.

An underlying pattern in all research up through and including Dyna-METRIC is that spares demands are driven on a purely flying hour or sortie basis. However, exercises, DESERT SHIELD/STORM, and recent research by HQ USAF and the LMI reveal all spares may not fail on a strictly flying hour or sortie basis. The problems introduced by forecasting demands based on inaccurate failure modes produce inadequate MRSP configurations, which significantly impact wartime support. The primary objective of this research is to align demands and failure modes at the work unit code level to hopefully improve spares demand forecasting. The methodology to accomplish this research is outlined in the next chapter, along with an explanation of our data and its origin.

III. Methodology

Introduction

The purpose of this study is to determine if demands or maintenance actions of reparable spares are related to cumulative flying hours and number of sorties at the work unit code level. If reparable demands, flying hours, and sorties are related at the work unit code level, this relationship could be used to develop more accurate reparable spare part demand forecasts, leading to economical and efficient Air Force MRSP configurations.

A detailed method is required to conduct a research study and achieve the study's purpose. The detailed method of conducting a study is termed the methodology. This chapter covers the methodology and outlines the research design, research questions, research hypotheses and instruments, and the process used for variable validation. The data collection, gathering, and sorting, population and sample size, and data limitations are also presented. The chapter concludes with a section covering implementation of the research design in a step-by-step sequence.

Research Design

A researcher must develop a distinct path to follow through the various phases of a study to successfully achieve the research objectives. This path is known as the research design. The research design provides three essential benefits to the research process:

> First, the design is a plan for selecting the sources and types of information used to answer the research question. Second, it is a framework for specifying the relationships between the study's variables. Third, it is a blueprint that outlines each procedure from the hypotheses to the analysis of the data. (Cooper and Emory, 1995:114)

Several different perspectives must also be considered in developing a research design. These perspectives include: degree of problem definition, method of data

collection, researcher control of variables, purpose of the study, time dimension, and topical scope (Cooper and Emory, 1995:115-117). Each of these perspectives will now be discussed in the context of how they correspond to the development of this research design.

The degree to which the problem is defined can be determined by the type of study to be conducted. The two types of studies are: an exploratory study and a formal study. Exploratory studies deal with discovering prospective research areas and developing testable hypotheses. A formal study is the follow-on process to the exploratory study and performs in-depth testing of the proposed exploratory hypotheses (Cooper and Emory, 1995:115). In the area of aircraft spares demand forecasting, significant research has already been conducted, particularly by the RAND Corporation, HQ USAF, and the Logistics Management Institute (LMI), as outlined in Chapter Two. A common theme of this prior research is that spares demand is influenced by operational aircraft measures, such as flying hours or numbers of sorties. A major distinction of this research study is the evaluation of the relationship between spares demand, or maintenance actions, flying hours, and number of sorties at the work unit code level. Because this research is a follow-on process to prior research, the study is considered a formal study.

Once the problem is defined and the type of study is determined, the method of data collection must be established. Data collection can be performed by two methods: through observation or through use of a survey. Observational data collection deals with using data recorded through observation of a process or activity. Survey data collection requires collecting responses from individuals through the use of questionnaires or survey instruments (Cooper and Emory, 1995:115).

This research study uses observational data collection. The source of data is the Reliability and Maintainability Information System (REMIS) maintenance and sortie database. REMIS data from May to December 1993 and February to June 1994 is used

and covers worldwide failures of F-15C reparable spares. The 1993 and 1994 data sets are extensive and each contain approximately 50,000 combined maintenance action and sortie images. REMIS data is used because it includes the sorties flown by an aircraft and the corresponding maintenance actions performed by support personnel. Thus, the maintenance actions, or demands, can be matched to the exact sortie which caused the failure. The REMIS data is also used to establish three primary variables for the research study. These variables are: demands, or maintenance actions, the cumulative number of flying hours and the number of sorties, which were observed for occurrences of the same work unit code on each particular aircraft.

Once the variables are established, researcher control of variables is categorized into either experimental design or ex post facto design. In experimental design, the researcher attempts to control variables in order to determine if any one variable affects any other variable. In ex post facto design, the researcher has no control over variables and reports findings based on given data and the interactions of the variables (Cooper and Emory, 1995:115-116). Relationships between maintenance actions, cumulative flying hours, and number of sorties will be determined based on quantities obtained from the REMIS data. Because variable values come directly from the REMIS data, and no researcher control over the variables is obtained, this study incorporates ex post facto design.

Although the variables in the study are defined from REMIS data, the purpose of the research study must also be defined. The purpose of a study can be either descriptive or causal. Descriptive studies attempt to answer the "Who, what, where, when, or how much?" within the objectives of the research. Causal studies focus on the question of "Why?" and attempt to demonstrate relationships between variables (Cooper and Emory, 1995:116). This research is a causal study that attempts to show a relationship, at the

work unit code level, between demands/maintenance actions, cumulative flying hours, and number of sorties .

Upon defining the purpose of the study, the time dimension of the study must be determined. The time dimension can be either cross-sectional or longitudinal. Cross-sectional studies are performed once and examine a specific instance in time. Longitudinal studies are carried out several times over a lengthy time period (Cooper and Emory, 1995:116). This research study is a cross-sectional study because it examines data from May to December 1993 and February to June 1994 and will only be performed a single time.

One of the primary areas in a research process involves study and analysis of the results, which can be thought of as the topical scope of the research. The topical scope of the research can take the form of a statistical study or a case study. Statistical studies, as explained by Cooper and Emory, "Are designed for breadth rather than depth. .... Hypotheses are tested quantitatively. Generalizations about findings are presented based on representativeness of the sample and the validity of the design" (Cooper and Emory, 1995:116). Case studies emphasize qualitative data and the "contextual analysis" of several events, which examine their underlying relationships (Cooper and Emory, 1995:116-117). The topical scope of this thesis research is a statistical study. The REMIS data is quantitative in nature. Also, hypotheses are developed and tested through the use of regression and Poisson process analysis techniques to determine whether or not a relationship exists between demands/maintenance actions, cumulative flying hours, and numbers of sorties at the work unit code level.

In summary, the research design used in this study was developed from the following perspectives. The research is a formal study using an observational data collection method. Ex post facto research design is used and the study is causal in nature. Finally, the study is cross-sectional in relation to time and the topical scope is statistical.

The step-by-step implementation of the research design is discussed in detail later in the chapter. The following section outlines the research questions.

Research Questions

To determine if a relationship exists between demands/maintenance actions, flying hours, and sorties at the work unit code level, the following research questions are developed for subsequent answer:

Research Question One. Is there a relationship between demands/maintenance actions, flying hours, and number of sorties at the work unit code level? To thoroughly develop an answer to the first research question, the following investigative questions will be addressed:

1. Are demands or maintenance actions, flying hours, and number of sorties correlated at the two digit level of specific work unit codes?

2. Do demands or maintenance actions, flying hours, and number of sorties show more, or less, correlation at the three, four, or five digit level of work unit codes, as compared to the two digit level?

The two, three, four, and five digit work unit code levels used in this study are thoroughly explained in Chapter One and Appendix A.

Research Question Two. The second research question is: Can decision rules be established to forecast demands/maintenance actions based on a spares work unit code alone? This question addresses matching the number of demands or maintenance actions to specific work unit codes, which can be used to estimate demand for reparable spares and establish MRSP configuration quantities. Research question two will be answered based on the extent of correlation obtained in analyzing and answering the first research question.

Research Hypotheses and Instruments

The initial relationship between demands or maintenance actions, cumulative flying hours, and number of sorties will be assessed through a three phase process, which uses multiple linear regression, Poisson regression, and fitting of a Poisson process. A three phase process is used to determine the best relationship between demands/ maintenance actions, cumulative flying hours, and number of sorties at the work unit code level. Multiple linear regression is appropriate in Phase One because it establishes probabilistic models that describe the linear relation between the criterion variable, demands/ maintenance actions, and the predictor variables, cumulative flying hours and number of sorties.

However, the criterion variable, demands/maintenance, represents discrete "counts" of the number of demands/maintenance actions. For the purposes of this study, the discrete "counts" of demands/maintenance actions are assumed to be a function of the predictor variables, cumulative flying hours and number of sorties. The counts of discrete events are normally modeled as a Poisson distribution. Thus, in Phase Two, Poisson regression is appropriate and considers the "count" nature of the criterion variable to determine whether or not a relationship exists between demands/maintenance actions, flying hours, and number of sorties. Of course, Poisson regression is based on the use of the Poisson distribution (Myers, 1990:333).

A Poisson process, which is also based on the Poisson distribution, is appropriate for Phase Three in order to model the discrete demands/maintenance actions occurring at the work unit code level for a specified quantity of flying hours or number of sorties. Poisson parameters are calculated from the 1993 data set and are used to estimate occurrences for the 1994 data set. Residual analysis is used to justify the fit of the Poisson process.

By using the three phase process, the first research question will be answered before attempting to answer research question two. The first research question establishes whether or not there is a relationship at the work unit code level between the criterion variable (demands/maintenance actions) and the predictor variables (cumulative flying hours and number of sorties). For the regression techniques, the determination of strong correlation between the criterion and predictor variables will be based on the coefficient of multiple determination (R^2) and hypotheses testing of the linear β coefficients in the regression models. The fit of the Poisson process will be evaluated from the residual analysis comparing actual 1994 demands/maintenance actions to expected demands/ maintenance actions and hypotheses testing. The overall goal is to obtain the model with the best fit. The three phases of the research design, multiple regression, Poisson regression, and a Poisson process, will now be presented.

Multiple Regression. The first order, "reduced," model of the multiple regression analysis will take the form: $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$. The criterion variable used for the multiple regression is demands/maintenance actions and is represented by Y. The predictor variables are cumulative flying hours, x_1, and number of sorties, x_2. The x_1 and x_2 are referred to as carriers because they carry information about Y within the regression model (Devore, 1991:526). The parameter β_0 is the Y intercept of the regression plane (Neter and Wasserman, 1985:227). The parameters β_1 and β_2 are referred to as the partial regression coefficients. β_1 indicates the mean response per unit increase in x_1, the cumulative flying hours, while β_2 indicates the mean response per unit increase in x_2, the number of sorties (Neter and Wasserman, 1985:228-229).

Upon obtaining the criterion and predictor variables from the data, multiple linear regression will be performed to determine whether or not demands/maintenance actions, cumulative flying hours, and number of sorties are correlated. The determination of strong correlation between the variables in the model will be based on the coefficient of

multiple determination, R^2, and hypotheses testing of the linear β coefficients in the regression models. The values of R^2 can range from 0 to 1. The higher the value of R^2, the greater the correlation between the variables in the regression model. If R^2 is equal to 1, the model fits the data perfectly and all observations fall directly on the fitted response surface (Neter and Wasserman, 1985:240).

Specific hypotheses will be tested for the "reduced" multiple regression models. The specific hypotheses test will be set up as follows:

$H_o : \beta_1 = \beta_2 = \ldots \beta_k = 0$

H_a : at least one $\beta_i \neq 0$ (i = 1,.......,k)

In testing $H_o : \beta_1 = \beta_2 = \ldots = \beta_k = 0$ against H_a : at least one $\beta_i \neq 0$ (i = 1,.......,k), the following test, referred to as the test of model utility, will be used:

Null hypothesis: $H_o : \beta_1 = \beta_2 = \ldots = \beta_k = 0$
Alternative Hypothesis: H_a : at least one $\beta_i \neq 0$ (i = 1,.......,k)
Test statistic value: $f = \dfrac{R^2 / k}{(1 - R^2) / [n - (k+1)]}$
Rejection region for a level α test: $f \geq F_{\alpha, k, n-(k+1)}$
R^2 = coefficient of multiple determination,
n = number of data points;
k = number of carriers. (Devore, 1991:535)

In evaluating the best regression model, cumulative flying hours, which is represented by coefficient β_1, and the number of sorties, which is represented by coefficient β_2, will either contribute or not contribute to the regression model depending on the outcome of the hypotheses tests in the test for model utility. For example, if the null hypothesis: $H_o : \beta_1 = \beta_2 = \ldots = \beta_k = 0$ is true, then neither cumulative flying hours or a number of sorties contribute to the model or correlate highly with demands/ maintenance actions (the criterion variable). However, if the alternative hypothesis, H_a : at least one $\beta_i \neq 0$ (i = 1,.......,k) is true, then either cumulative flying hours, number of

sorties or both contribute to the model. If the alternate hypotheses is true, comparison of p-values to an $\alpha = 0.05$ will be used to determine which variables contribute to the "reduced" model. Variables with p-values greater than 0.05 will be considered as non-contributing factors in any "reduced" multiple regression models.

In order to determine whether additional carriers contribute to the "reduced" model, the "reduced" model will be tested against a "full" model. The "full," second order, interaction multiple regression model, containing all higher order or interaction variables, takes the following form: $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$. x_1^2 represents cumulative flying hours squared. x_2^2 represents the number of sorties squared. $x_1 x_2$ represents the linear combination of cumulative flying hours and number of sorties. β_3, β_4, and β_5 are the corresponding regression coefficients. The hypotheses to be tested are:

H_o : model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$ (reduced model)

H_a : model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$ (full model)

In testing H_o versus H_a, the following test will be used:

Test Statistic value: $f = \dfrac{(SSE1 - SSE2)/p}{MSE2}$

Rejection region: $f \geq F_{\alpha, n-k-1}$

SSE1 = the unexplained variation for the reduced model.
SSE2 = the unexplained variation for the full model.
MSE2 = Residual Mean Square Error from full model.
n = the number of points.
k = the number of regressor variables in the full model.
p = the number of additional regressor variables added to the reduced model to obtain the full model.

(Devore, 1991:536)

If H_a is true, indicating the full model is more appropriate, comparison of p-values to an $\alpha = 0.05$ will be used to determine which higher order or interaction variables contribute to the full model.

A residual will be calculated for the resulting multiple regression model. The residual is the difference between the actual value of demands/maintenance actions, obtained from the 1994 validation data, and the expected number of maintenance actions obtained from applying 1994 flying hour and sortie values to the regression model built from the 1993 data. As Devore explains, "If the residuals are small in magnitude, then much of the variability in observed Y values appears to be due to the linear relationship of the variables in the model and Y, while large residuals suggest quite a bit of inherent variability in Y relative to the amount due to the linear relation" (Devore, 1991:464).

Tests for normality and autocorrelation will also be performed on the regression models. The test for normality will be performed using the Wilk-Shapiro/Rankit Plot. To test for autocorrelation, the Durbin-Watson test will be used. Autocorrelation is the positive correlation of the regression model error terms over time. The Durbin-Watson test determines if variables in the model need to be transformed. The Durbin-Watson test is also used to determine whether or not additional higher order terms, such as x^2 or x^3, need to be added to the model to correct the autocorrelation problem. If autocorrelation is a problem in the regression model, multicollinearity effects could result through the addition of extra variables. When the independent variables in a regression model are correlated among themselves, the variables exhibit intercorrelation, or what is known as multicollinearity (Neter and Wasserman, 1985:250). An indication of multicollinearity is represented by large changes in the Beta coefficients, when independent variables are added to the model. After analyzing the data with multiple regression, Poisson regression will be used in Phase Two.

Poisson Regression. Poisson regression will be used to evaluate the mean number of demands/maintenance actions, as a parameter of the Poisson distribution. The demands/maintenance actions are assumed to represent a Poisson mean and are a function of the predictor or regressor variables, cumulative flying hours and number of sorties.

The model for Poisson regression is represented as follows:

$$p(y_i;\beta) = \frac{e^{-t_i[\mu(x_i,\beta)]}[t_i\mu(x_i,\beta)]^{y_i}}{y_i!} \qquad (\text{i} = 1,2, \ldots\ldots, \text{n})$$

The function $\mu(x_i;\beta)$ represents the Poisson mean and is referred to as the link function. The t is assumed to be 1 because the "basis" is taken as a single type of aircraft, the F-15C. The link function relates the predictor or regressor variables to the distribution mean and must always be nonnegative, as well as, user specified (Myers, 1990:334). For this study, the Statistix analytical software package will be used to perform the Poisson regressions and the link function is chosen to be represented by $x_i'\beta$ where $x_i'\beta > 0$. x_i' and β are vectors containing the variables and estimated regression coefficients.

Poisson regression uses an iteratively reweighted least squares technique to produce the maximum likelihood estimators for the regression coefficients in β (Myers, 1990:335). After estimation of the regression coefficients, the Poisson regression model is represented as follows:

$$\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_k x_k$$

$\hat{\mu}$ is the estimate of the mean number of demands or maintenance actions. $\hat{\beta}_0, \hat{\beta}_1$, and $\hat{\beta}_2$ are the maximum likelihood estimates of the regression coefficients. x_1 represents the cumulative flying hours, while x_2 represents the number of sorties.

The primary measure of fit in Poisson regression is the deviance. "The deviance plays a role similar to the residual error in linear regression. The deviance can be thought

of as the "distance measure" between the fitted model and the actual data - the smaller, the better" (Statistix, 1985:183).

In analyzing the data in this study, three Poisson regressions will be performed against specific work unit code levels. Initially, two Poisson regressions will be run, one for cumulative flying hours and one for number of sorties. The third Poisson regression will include both cumulative flying hours and number of sorties. The model with the smallest deviance will be used to estimate demands or maintenance actions from the 1994 validation data set. Comparison testing of p-values to an $\alpha = 0.05$ will determine which variable coefficients actually contribute to the resulting Poisson regression model. If p is less than or equal to $\alpha = 0.05$, the variable contributes to the model. If p is greater than $\alpha = 0.05$, the variable does not contribute to the model. A residual will also be calculated for the resulting Poisson regression model. After performing the Poisson regressions, the last segment of the research design, a Poisson process, will be attempted.

Poisson Process. A Poisson process represents a random variable, such as the total number of demands/maintenance actions, that occur during a specified period of time or within a specified region, for example, a period of flying hours or number of sorties. In order to justify and fit a Poisson process, three conditions must be achieved:

1. The number of occurrences in any two disjoint intervals of time must be independent of one another (Degroot, 1986:254). For instance, although an aircraft may break several times over a specified time period, the probability that at least one break will occur in an upcoming time interval is unchanged.

2. The probability of an occurrence during a smaller time interval must be approximately proportional to the length of the interval. In other words, the process is assumed to be stationary over time (Degroot, 1986:255). This study deals with aircraft data that experience both surges and lulls in operations, which possibly violates this

condition. However, it is assumed over the long-term that steady state conditions prevail and the second Poisson process condition is satisfied.

3. The probability that there will be two or more occurrences in any particular very short interval of time must have a smaller order of magnitude than the probability that there will be just one occurrence (Degroot, 1986:255). Therefore, it is assumed that the probability of two demands or maintenance actions in a small interval is negligible in comparison to the probability of one demand or maintenance action.

In achieving the three conditions listed above, the number of demands or maintenance actions in a fixed interval of time, t, will have a Poisson distribution and the mean is represented by λt. For this study, λ is a positive constant and is the expected number of demands or maintenance actions per cumulative flying hours or number of sorties. Thus, if X is a random variable representing the number of demands or maintenance actions, and has a Poisson distribution with parameter λ, the expected value of X, E(X), is equal to the variance of X, V(X), which both equal λ (Devore, 1991:120).

In evaluating the data sets in this study by fitting a Poisson process, λ 's based on both flying hours and sorties will be calculated from a 1993 data set for specific two digit work unit code levels. The 1993 λ factors will be multiplied by cumulative flying hours and number of sorties, which are obtained from a 1994 validation data set. The resulting, expected number of two digit work unit code maintenance actions will be compared to the actual number of corresponding two digit work unit code maintenance actions in the 1994 data set. A residual will be calculated for the Poisson process by taking the actual number of maintenance actions and subtracting the expected number of maintenance actions. The closer the residual value is to zero, the better the estimation and fit of the Poisson process.

To use a model based on the Poisson process, similar conditions must be maintained between timeframes as outlined in condition two above. Thus, to ensure the demand rates are similar for the 1993 and 1994 data sets, hypotheses testing will be

performed. The null hypothesis, $H_o: \lambda_{93} = \lambda_{94}$, the 1993 and 1994 demand rates are the same, will be tested against $H_a: \lambda_{93} \neq \lambda_{94}$, the 1993 and 1994 demand rates are different, for each two digit work unit code level. The two sample, two sided F-test for equal population variances will be used to test the hypotheses because under the assumption of a Poisson distribution, the mean equals the variance, which both equal λ.

Upon analyzing the data with multiple regression, Poisson regression, and fitting a Poisson process, a comparison of residuals will be performed to determine which technique produces the best estimates of expected demands/maintenance actions. After an appropriate regression model or Poisson process estimation has been developed for the specific work unit code levels, the results will be analyzed to address research questions one and two.

Variable Validation

Variable validation ensures only variables which contribute to the linear regression models are included in the models. The available REMIS data allows for computation of the criterion variable, demands/maintenance actions, and the predictor variables, cumulative flying hours and number of sorties occurring at the work unit code level. These variables were selected because demands/maintenance actions, cumulative flying hours, and number of sorties are the only variables readily obtainable from the REMIS database. Although additional variables may contribute to the relationship between demands/maintenance actions, flying hours, and sorties, these additional variables were not available. Also, the major B-52 regression study conducted by H.S. Campbell in 1963 did consider additional variables other than flying hours and sorties. However, the results indicated the additional variables did not significantly contribute to the regression models (Campbell, 1963:vi). Nevertheless, based on the HQ USAF/LMI research covered in Chapter One, spares demand is now believed to fall somewhere between the pure sortie

and pure flying hour curves. Therefore, flying hours and sorties were chosen as the predictor or estimation variables.

The predictor variables are validated through the use of multiple regression and the comparison of the f-statistic to the critical rejection regions. Poisson regression or Poisson process procedures are also used as sources of variable validation. In building the linear regression models, the predictor variables are added in the multiple regression and additions of higher order variables are tested through the use of the full model. Depending on the outcome of hypothesis testing and deviance values, p-value comparisons to an $\alpha = 0.05$ also validate which variables do and do not contribute to the regression models.

Data Collection, Gathering, and Sorting

The method of data collection is observational. Two databases are used in this study and were received from Mr. Michael Slay at the Logistics Management Institute (LMI). The analysis database contains worldwide REMIS data on the F-15C for the period May to December 1993. The validation database contains F-15C REMIS data for the period February to June 1994. The following data discussion focuses on the 1993 data set. However, similar procedures were used to set up and manipulate the 1994 data set.

The 1993 F-15C REMIS analysis data was separated into two distinct files, one covering maintenance data and the other covering sortie data. REMIS compiled the data from the base level Consolidated Aircraft Maintenance System (CAMS) for worldwide USAF bases who operate the F-15C. The maintenance database covers maintenance actions performed on the F-15C during the specified timeframe. Inclusive in this database is the following information: tail number, Julian date, work unit code, action taken code, when discovered code, how malfunctioned code, the beginning time for maintenance, sortie number, sortie length, sortie mission, days from sortie to maintenance, the number

of sorties, and the Stock Record Account Number (SRAN) of the base assigned the specific aircraft. The sortie database lists all sorties of each F-15C for the applicable timeframe. Inclusive in this database is the following information: tail number, sortie, Julian date, sortie number, mission code, sortie length, number of sorties, and SRAN.

Both the 1993 maintenance and sortie databases were transferred to a mainframe VAX computer in order to use the sorting capabilities of the Statistical Analysis System (SAS). This transfer was necessary due to the combined size of both data files (over 58,000 images), which was too large for a personal computer to handle. The maintenance file was initially sorted by work unit code to identify which specific aircraft tail numbers contained which work unit codes. Also, each aircraft tail number represented in the maintenance file could possibly have several occurrences of the same work unit code. To track which sortie actually resulted in the maintenance action of each specific work unit code, fields from the maintenance database were matched against similar fields in the sortie database. Once the match was complete, both the maintenance and sortie files were merged together into one file. The merged file allowed for the tracking of which sortie resulted in a maintenance action and also allowed for easy calculation of the number of maintenance actions, cumulative flying hours, and number of sorties experienced by each aircraft in the database. However, a lack of maintenance action data on 160 of the aircraft in the 1993 data set made it impossible to track which aircraft sortie resulted in a maintenance action on the aircraft. Therefore, these 160 aircraft were deleted from the 1993 database. The remaining 1993 data set population covered 247 aircraft. The 1994 data set had no missing maintenance action data and contained 340 aircraft.

A FORTRAN program was written to query the merged file and calculate the number of maintenance actions at the 2, 3, 4, and 5 digit work unit code level for each aircraft tail number in the data set. The FORTRAN program also calculates the cumulative flying hours and number of sorties for each aircraft in the data set. The

FORTRAN program produces files each containing 247 records for the 1993 data set and 340 records for the 1994 data set, which represent the number of aircraft in each data set. Each data record contains the following fields: aircraft tail number (TAIL), work unit code (WUC), demands (DMDS)/maintenance actions (or the number of occurrences of the specific work unit code), cumulative flying hours (CUMFH), number of sorties (NSORT), cumulative flying hours squared (CUMFH2), number of sorties squared (NSORT2), and cumulative flying hours times number of sorties (FHNSORT or CUMFHNSORT). The files generated by the FORTRAN program, representing each work unit code level, were transferred into Statistix format and used to perform the regression and Poisson process analysis in the study. The SAS programs used to merge and sort the 1993 and 1994 data are included in Appendix B. The FORTRAN programs are included in Appendix C, along with a sample of 1993 and 1994 data output files.

Population and Sample Size

The 1993 and 1994 maintenance and sortie databases contain information on a single type of aircraft, the F-15C. The 1993 maintenance database totals 12,989 individual entries. The 1993 sortie database contains 45,770 entries. After deleting the 160 aircraft that had no corresponding maintenance history in the 1993 sortie database, the resulting sortie/maintenance action, merged file still contains 32,240 entries for the eight month time period.. The 1994 maintenance database contains 25,177 individual entries. The 1994 sortie database contains 23,079 entries for the five month period. Only failures of reparable spares are considered within the data.

Data Limitations

The data is limited in scope because it only includes one type of fighter aircraft, the F-15C for the periods May to December 1993 and February to June 1994. In analyzing the data, regression and Poisson process analyses will be run against the criterion variable,

demands/maintenance actions, and the predictor variables, cumulative flying hours and number or sorties, created for each work unit code level. However, the number of regressions will be limited due to the frequency of individual work unit code occurrences. Initial sorting of the data files indicated several work unit codes show only a small number of occurrences within the data sets, which implies low demand rates. Meaningful regression results cannot be achieved by regressing on only two or three points. The lack of significant numbers of specific work unit code occurrences will limit the work unit codes available for development of work unit code decision rules.

Despite the small number of occurrences for specific work unit codes, some of the individual work unit codes have larger number of occurrences. In obtaining a representative sample across all work unit codes, only those work units code levels with more than 30 occurrences will be evaluated. The 30 occurrences limit was established to ensure there were enough points in the regression and Poisson process analysis to provide meaningful results. Performing a regression or Poisson process analysis on only a few points (less than 30) would probably not produce meaningful results. A solution to the problem of limited occurrences at the four and five digit work unit code levels is to aggregate the work unit codes at the two or three digit level.

Also, the number of predictor variables is limited within the data. The available predictor variables are cumulative flying hours and number of sorties. However, additional carriers can be added to full regression models by squaring or linearly combining these predictor variables. Transformations of the data may also be necessary due to a lack of correlation (small R^2 values).

Because the timeframe covered by the data is discrete, the first maintenance action obtained on each aircraft for specific work unit codes will only accumulate flying hours and sorties from the starting point of the data set. Based on this limitation, the total number of maintenance actions experienced by each aircraft is calculated for the

cumulative flying hours and number of sorties flown during the discrete timeframe covered by the data set. A more accurate analysis could possibly consider time between maintenance actions, however, the limited number of occurrences of specific work unit codes precludes this type of analysis.

Research Design Implementation

The research design is implemented in three phases. Phase One covers multiple regression. Phase Two deals with Poisson regression, while Phase Three relates use of a Poisson process. In each phase, the data files obtained from the FORTRAN programs are used to obtain points for the multiple or Poisson regressions or parameters for the Poisson process. The three research design phases are intended to answer the first research question: "Is there a relationship between demands/maintenance actions, flying hours, and number of sorties at the work unit code level?" The steps of each research design phase will now be presented.

Phase One: Multiple Regression. In building a multiple regression model, a four stage process will be followed:

Stage One: Data collection and preparation

Stage Two: Reduction of the number of independent variables

Stage Three: Model refinement and selection

Stage Four: Model Validation (Neter and Wasserman, 1985:433)

To implement the four stage model building process, the following steps will be used:

Step 1: Obtain FORTRAN files from the 1993 data set for each specific two, three, four, and five digit work unit code level. Transfer the files into Statistix format in order to perform multiple regression analysis.

Step 2: Establish the criterion and predictor variables from the data. The criterion variable is the number of demands or maintenance actions experienced by each aircraft. The predictor variables are the cumulative number of flying hours and number of sorties flown by each aircraft. Each aircraft tail number in the data set represents a point on the regression plane.

Step 3a: Using Statistix Analytical software, perform multiple linear regression on the first order, "reduced" regression model. Use the test for model utility and *f*-statistic/ F-Distribution procedures to test the following hypotheses for each specific two, three, four, and five digit work unit code level:

H_o : $\beta_1 = \beta_2 = \ldots \beta_k = 0$

H_a : at least one $\beta_i \neq 0$ ($i = 1, \ldots\ldots, k$)

If H_a is true, use p-value comparisons to an $\alpha = 0.05$ to determine which variables contribute to the reduced model.

Step 3b: Perform multiple regression in Statistix on the "full," second order, interaction model. Use *f*-statistic/F-Distribution procedures to test the following hypotheses:

H_o : model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$ (reduced model)

H_a : model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$ (full model)

If H_a is true, use p-value comparisons to an $\alpha = 0.05$ to determine which variables contribute to the full model.

Step 4: To validate the model, a residual will be calculated from the 1994 data set. Using the reduced or full model obtained from the 1993 data, substitute 60,254.5 flying hours for x_1, the cumulative flying hours, and 38,666 sorties for x_2, the number of sorties. The 1994 data set has a total of 60,254.5 flying hours and 38,666 sorties. The value of Y obtained from the 1993 regression model, using the 1994 flying hour and sortie values, is the expected number of maintenance actions for 60,254.5 flying hours and

38,666 sorties. Compare the expected value of 1994 maintenance actions to the actual number of 1994 maintenance actions. The actual value minus the expected value is the residual.

Phase Two: Poisson Regression. Phase two of the research design implementation involves Poisson regression. Poisson regression will be performed according to the following steps:

Step 1: Obtain FORTRAN files from the 1993 data set for each specific two, three, four, and five digit work unit code level. Transfer the files into Statistix format in order to perform Poisson regression analysis.

Step 2: Perform three separate Poisson regressions on the two digit level work unit code files. The first regression will only include cumulative flying hours as a predictor variable. The second regression will only include number of sorties as the predictor variable. The final regression will include both cumulative flying hours and number of sorties as predictor variables.

Step 3: Compare deviance values and select the model with the smallest deviance. The smaller the value of the deviance, the better the fit of the Poisson regression model. Use p-value comparisons to an $\alpha = 0.05$ to determine which variables contribute to the full model.

Step 4: Similar to the multiple regression analysis, calculate a residual using the model with the smallest deviance and the 1994 cumulative flying hour and sortie values of 60,254.5 and 38,666, respectively.

Phase Three: Poisson Process. Phase three of the research design implementation fits a Poisson process to the data. The Poisson process will be fit according to the following steps:

Step 1: Calculate the λ values for the Poisson process from the 1993 data set on the basis of flying hours and sorties. λ will take the following form: the cumulative 1993

maintenance actions at a specific two digit work unit code level divided by either cumulative flying hours or total number of sorties.

Step 2: Use the 1993 λ values from Step 1 to calculate the expected number of maintenance actions for the 1994 data set, based on flying hours and sorties. (Multiply the 1993 flying hour or sortie based λ values by 60,254.5 flying hours or 38,666 sorties).

Step 3: Calculate a +/- 2σ confidence interval for the Poisson process, based on flying hours or sorties. Note: If X is a random variable and has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$. Thus, $\sigma = \sqrt{\lambda}$.

Step 4: Calculate the probability that the number of maintenance actions is below the lower bound of the confidence interval or above the upper bound of the confidence interval for both the flying hour and sortie based models.

Step 5: Compare the actual number of 1994 maintenance actions, for each specific two digit work unit code level, with the expected values calculated from Step 1 above to obtain a residual based on flying hours and sorties.

Step 6: Use the two-sample, two sided F test for equal population variances to perform the hypotheses test $H_0{:}\lambda_{93} = \lambda_{94}$ versus $H_a{:}\lambda_{93} \neq \lambda_{94}$.

The residual results from the three phases of the research design implementation will also be analyzed/compared to determine which method produces the best models and exhibits a relationship between demands/maintenance actions, flying hours, and sorties at the work unit code level. Upon analyzing the data by multiple regression, Poisson regression, and fitting a Poisson process, research question two: "Can decision rules be established to forecast demands/maintenance actions based on a spares work unit code alone?" will be answered based on the best regression model or Poisson process estimation obtained from the resulting three phase residual analysis.

Summary

This chapter outlines the research methodology of this study. The chapter also describes the research design, research questions, research hypotheses and instruments, and the process used for variable validation, as well as, the data collection, data gathering, population and sample size, and limitations of the data. The final section of the chapter discusses the implementation of the research design. The research design and methodology are based on multiple linear regression, Poisson regression, and fitting of a Poisson process, which are used to determine if a relationship exists between demands/ maintenance actions, cumulative flying hours, and number of sorties at the work unit code level. The implementation of the research design attempts to develop a best regression model or Poisson process estimation technique to align demands, or maintenance actions, flying hours, and sorties at the work unit code level. The next chapter presents the results, and analysis of these results, which were obtained from implementing this research methodology and design.

IV. Results and Analysis

Introduction

This chapter presents the results obtained from implementing the three phases of the research methodology. The results obtained from multiple regression, Poisson regression, and fitting of a Poisson process will be initially reviewed and discussed. Following the review of the research results, an analysis/comparison of residuals obtained from multiple regression, Poisson regression, and fitting of a Poisson process is also presented to determine which method is most suitable in explaining any relationship between demands, flying hours, and number of sorties at the work unit code level.

Multiple Regression Results

Multiple regressions were performed against specific two, three, and five digit levels of the work unit code. The four digit level of the work unit code was not analyzed due to the close similarity with results obtained at the five digit work unit code level. Multiple regressions were performed on 24 different two digit work unit code levels, 74 different three digit work unit code levels, and 115 different five digit work unit code levels. Tables D-1, D-2, and D-3 in Appendix D list the work unit code levels along with the coefficient of multiple determination, R^2, values and Durbin-Watson statistics obtained from the multiple regression analysis.

A majority of the multiple regression models produced very small R^2 values. The small R^2 values are believed to be caused by a lack of data points at lower levels of the work unit code. For example, at the two digit level, all work unit codes beginning with the same first two digits are used in the regression. However, at the five digit level, only those work unit codes with exactly the same five digits are used. The result is more data points at the two digit versus the five digit level of the work unit code.

Due to the lack of regression points and any significant correlation, only those two digit work unit code levels with an R^2 approximately equal to or greater than 0.200 were analyzed by hypotheses and residual testing. The two digit work unit codes which met this criterion are: 13, 23, 63, 74, and 76. Table 4-1 lists the results of the multiple regression analysis and hypotheses/residual testing.

Table 4-1. Multiple Regression Results

Two-Digit WUC Level	R^2	Reduced Model Hypoth. Test	Result	Reduced vs. Full Model Hypotheses Test	Result	Actual # of 1994 Maint. Actions	Expected # of Maint. Actions	Residual; Actual - Expected
13	0.2901	$Ho{:}\beta_i = 0$ $Ha{:}\beta_i \neq 0$	Enough evidence to reject Ho	Ho:Reduced Model Ha: Full Model	Not enough evidence to reject Ho	2,092	1,321	771
23	0.2134	$Ho{:}\beta_i = 0$ $Ha{:}\beta_i \neq 0$	Enough evidence to reject Ho	Ho:Reduced Model Ha: Full Model	Enough evidence to reject Ho	2,069	Not Calculated	Not Calculated
63	0.1999	$Ho{:}\beta_i = 0$ $Ha{:}\beta_i \neq 0$	Enough evidence to reject Ho	Ho:Reduced Model Ha: Full Model	Not enough evidence to reject Ho	1,057	976	81
74	0.3492	$Ho{:}\beta_i = 0$ $Ha{:}\beta_i \neq 0$	Enough evidence to reject Ho	Ho: Reduced Model Ha: Full Model	Not enough evidence to reject Ho	3,710	3,262	448
76	0.2522	$Ho{:}\beta_i = 0$ $Ha{:}\beta_i \neq 0$	Enough evidence to reject Ho	Ho: Reduced Model Ha: Full Model	Not enough evidence to reject Ho	1,842	1,083	759

For two-digit work unit code level 23, the expected number of maintenance actions and residual were not calculated due to the outcome of the reduced versus full hypotheses test. In this test, enough evidence existed to accept the full model. However, none of the variables in the full model passed the p-value comparison to an $\alpha = 0.05$. Therefore, no predictive model was available for two digit work unit code level 23. Detailed

calculations of the multiple regression hypotheses testing and residual analysis are included in Appendix D.

Although multiple regression models were built and analyzed at the two digit work unit code level, the small R^2 values and the large residuals indicate a limited linear relationship exists between the criterion variable, demands/maintenance actions, and the predictor variables, cumulative flying hours, and number of sorties at the work unit code level. The lack of correlation is also portrayed in the multiple regression residual plots. Figure 4-1 shows a residual plot for two digit work unit code level 76. The residual plot appears to be stratified into layers because the demands/maintenance actions, used as the criterion variable in the multiple regression, are integer numbers representing the numbered counts of demands/maintenance actions.

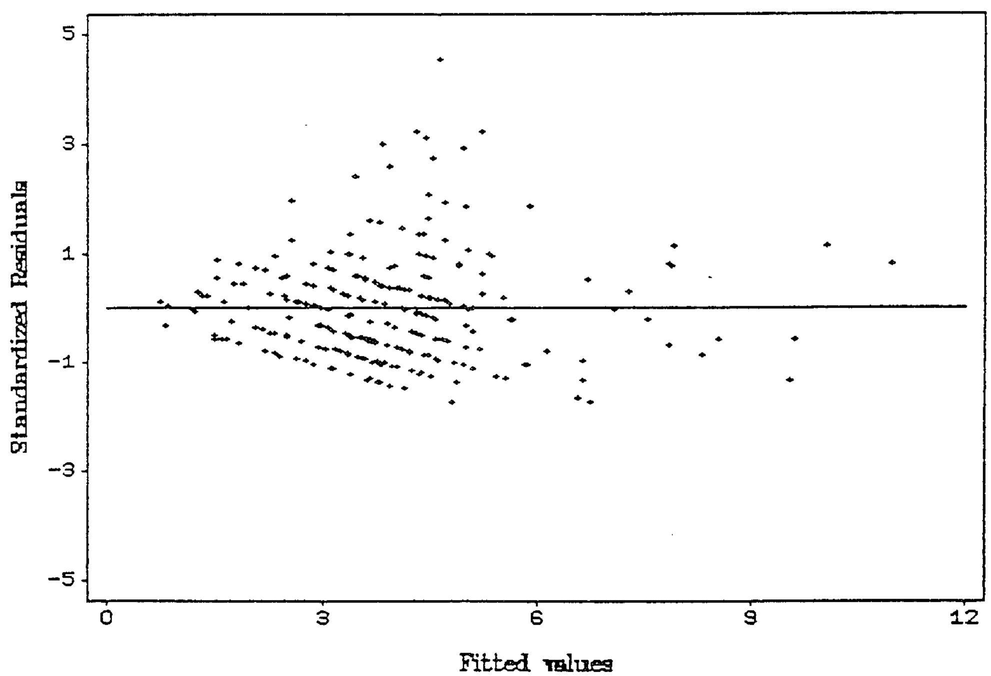

Figure 4-1. Residual Plot for Two Digit Work Unit Code Level 76, Electronic Countermeasures Components

To account for the "count" nature of the data represented by the criterion variable, demands/maintenance actions, Poisson regression was attempted to improve upon the multiple regression results. The results of the Poisson regression analysis are presented in the next section.

Poisson Regression Results

Three Poisson regressions were performed against the 24 different, two digit work unit code levels. The first Poisson regression included only cumulative flying hours (CUMFH) as a predictor variable, while the second Poisson regression included only the number of sorties (NSORT) as the predictor variable. The third Poisson regression contained both cumulative flying hours and number of sorties as predictor variables. The results of the Poisson regressions and residual analysis are presented in Table 4-2 on the next page. The Poisson regression calculations are included in Appendix E.

The measure of fit for a Poisson regression model is known as the deviance. The deviance is considered the "distance measure" between the fitted Poisson regression model and the actual data. The smaller the value of the deviance, the better the fit of the model (Statistix, 1985:183). As can be seen from Table 4-2, none of the three Poisson regressions models built for any of the two digit work unit code levels obtained small deviance values. For purposes of this study, a small deviance is considered 50 or less. Nevertheless, a residual was calculated for the Poisson regression model having the smallest deviance value for each two digit work unit code level.

Poisson regression is designed to handle data of a count nature. However, Poisson regression produced no better results than obtained through multiple linear regression. In reviewing simple scatter plots of the data, the absence of a linear relation is thought to be caused by a lack of data structure. Figures 4-2 and 4-3 on page 4-6 show two scatter plots of the study data, which exhibit the lack of data structure. Each point on

Table 4-2. Poisson Regression Results

2-Digit Work Unit Code Level	CUMFH Model Deviance	NSORT Model Deviance	CUMFH & NSORT Model Deviance	# of Actual 1994 Maint. Actions	# of Expected Maint. Actions	Residual; Actual - Expected
11	412.07	396.26	392.74	794	396	398
12	340.55	312.95	302.94	318	441	-123
13	658.90	537.38	482.11	2,092	265	1,827
14	493.65	474.59	457.61	1,121	213	908
23	557.00	470.06	461.35	2,069	323	1,746
24	572.59	542.59	534.23	1,114	253	861
41	450.63	438.33	438.23	667	268	399
42	507.07	486.57	485.37	766	367	399
44	464.08	421.76	407.13	665	292	373
45	350.79	331.30	329.95	965	453	512
46	360.49	359.30	350.02	808	393	415
47	314.66	289.90	286.50	280	635	-355
49	196.69	191.46	190.81	118	473	-355
51	456.33	417.93	417.74	1,043	300	743
52	431.70	425.82	425.81	284	239	45
55	513.65	502.07	492.14	502	201	301
57	223.38	221.77	202.70	265	53	212
63	526.33	449.66	440.93	1,057	352	705
65	542.55	535.90	530.10	771	267	504
71	546.29	512.32	512.32	1,049	314	735
74	840.81	628.75	619.26	3,710	332	3,378
75	566.99	542.15	518.77	725	200	525
76	489.07	528.86	483.65	1,842	274	1,568
97	482.82	477.31	467.16	476	143	333

the scatter plots represents one aircraft from the 1993 data set, which flew a specified quantity of flying hours and number of sorties, while producing a given number of demands, or maintenance actions. The pattern exhibited on the scatter plots is similar to the stratified effect produced on the multiple regression residual plots (See Figure 4-1).

With data structured in this manner, the fitting of a linear relation is difficult at best. For example, consider a specified number of flying hours or sorties on either Figure 4-2 or 4-3. For any value of flying hours or sorties, the number of demands (or

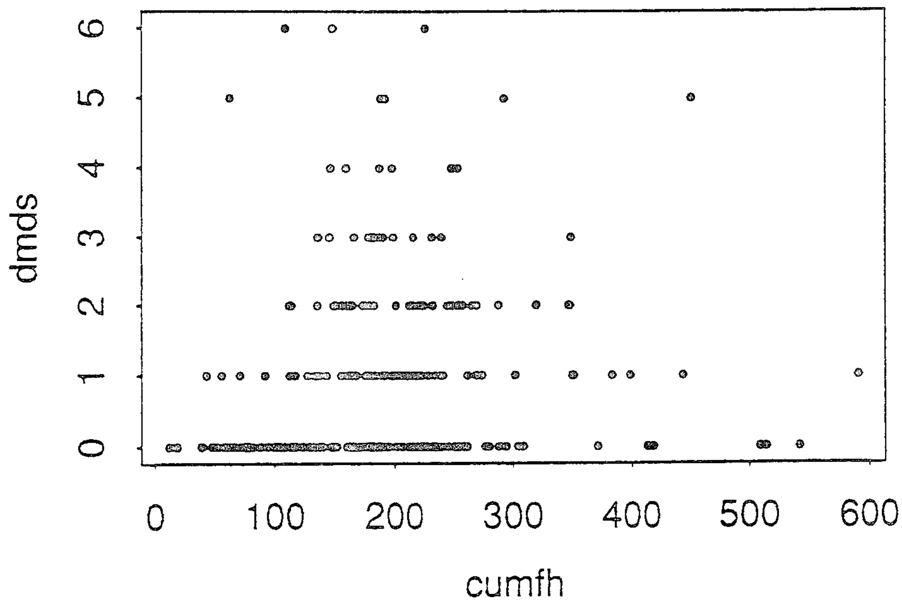

Figure 4-2. Scatter Plot of Demands versus Cumulative Flying Hours for Two Digit Work Unit Code Level 11, Airframe

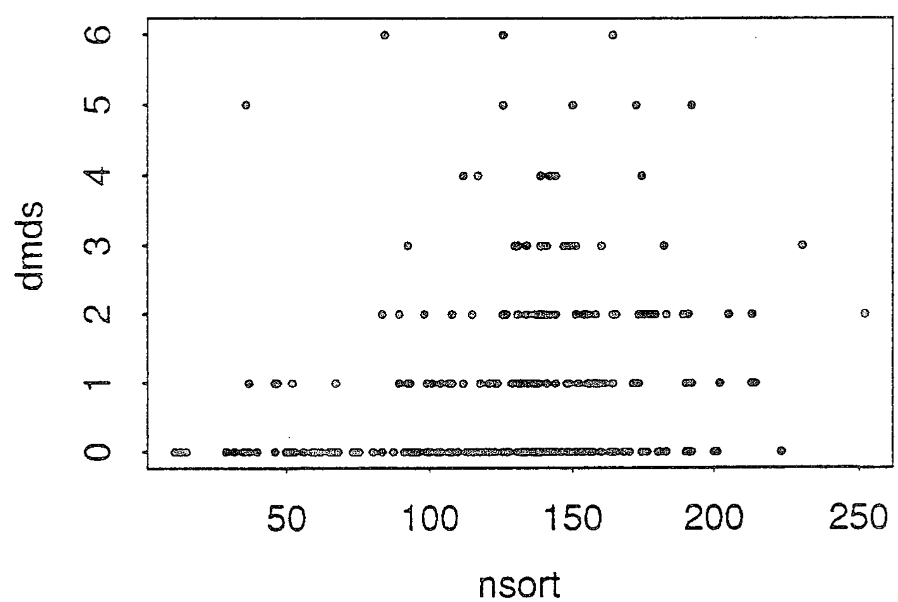

Figure 4-3. Scatter Plot of Demands versus Number of Sorties for Two Digit Work Unit Code Level 11, Airframe

maintenance actions) can range between 0 and 6. Therefore, attempting to fit a linear model produces small R^2 values in multiple linear regression and large deviance values with Poisson regression.

Based on the lack of correlation obtained with either multiple or Poisson regression, the data in the study were analyzed by fitting a Poisson process in an attempt to determine a relation between demands, or maintenance actions, cumulative flying hours, and number of sorties at the work unit code level. The results of the Poisson process analysis are covered in the next section.

Poisson Process Results

The Poisson process analysis was performed against each two digit work unit code level. The results of this analysis are contained in Tables 4-3 and 4-4, which are presented on the next two pages. Table 4-3 covers results for flying hour based lambda's while Table 4-4 covers results for sortie based lambda's. Detailed calculations for the Poisson process are included in Appendix F.

The Poisson process lambdas were calculated on the total demands, or maintenance actions, at each two digit work unit code level for all 247 aircraft in the 1993 data set. This process is a slightly different method than the regression procedures which considered each aircraft in the data set as a point for the regression. The probabilities calculated in Tables 4-3 and 4-4 show there is between a 4 and 5 percent probability that a value will fall outside the bounds of the computed confidence intervals. However, in 23 of the 24 cases, for both the flying hour and sortie based Poisson processes, the actual 1994 value fell outside the bounds of the computed confidence interval. Thus, only one two digit work unit code level, level 65, IFF, falls within the computed $+/-2\sigma$ confidence interval. Also, the Poisson process residuals comparing actual to expected numbers of demands/maintenance actions are rather large. The confidence interval results and large

residual values indicate that a Poisson process may not explain the relationship between demands/maintenance actions, flying hours, and number of sorties at the work unit code level.

Table 4-3. Poisson Process Results (Flying Hour Based)

Two-Digit WUC Level	1993 Flying Hour Based Lambda	Expected Number of Maint. Actions	+/- 2σ Confidence Interval; (Lower bound, Upper Bound)	Probability (X ≤ Lower bound or X ≥ Upper bound)	Actual # of 1994 Maint. Actions	Residual; Actual - Expected
11	0.0049	295	(260,329)	0.04463	794	499
12	0.0028	169	(143,195)	0.04539	318	149
13	0.0323	1,946	(1,858,2,034)	0.04606	2,092	146
14	0.0065	392	(352,431)	0.04588	1,121	729
23	0.0212	1,277	(1,206,1,349)	0.04544	2,069	792
24	0.0097	584	(536,663)	0.04482	1,114	530
41	0.0062	374	(335,412)	0.04632	667	293
42	0.0062	374	(335,412)	0.04632	766	392
44	0.0098	590	(542,639)	0.04592	665	75
45	0.0038	229	(199,259)	0.04736	965	736
46	0.0058	349	(312,387)	0.04481	808	459
47	0.0028	169	(143,195)	0.04539	280	111
49	0.0010	60	(45,76)	0.04597	118	58
51	0.0155	934	(873,995)	0.04592	1,043	109
52	0.0037	223	(193,253)	0.04446	284	61
55	0.0041	247	(216,278)	0.0485	502	255
57	0.0013	78	(61,96)	0.04801	265	187
63	0.0155	934	(873,995)	0.04592	1,057	123
65	0.0132	795	(739, 852)	0.04513	771	-24
71	0.0125	753	(698,808)	0.04503	1,049	296
74	0.0547	3,296	(3,181,3,411)	0.04516	3,710	414
75	0.0096	578	(530,627)	0.04372	725	147
76	0.0201	1,211	(1,142,1,281)	0.04584	1,842	631
97	0.0036	216	(187,246)	0.04505	476	260

Table 4-4. Poisson Process Results (Sortie Based)

Two-Digit WUC Level	1993 Sortie Based Lambda	Expected Number of Maint. Actions	+/- 2σ Confidence Interval; (Lower bound, Upper Bound)	Probability ($X \leq$ Lower bound or $X \geq$ Upper bound)	Actual # of 1994 Maint. Actions	Residual; Actual - Expected
11	0.0074	286	(252,320)	0.04435	794	508
12	0.0042	162	(137,188)	0.04534	318	156
13	0.0487	1,883	(1,796,1,970)	0.04497	2,092	209
14	0.0098	379	(340,418)	0.0451	1,121	742
23	0.0319	1,233	(1,163,1,304)	0.0447	2,069	836
24	0.0147	568	(521,616)	0.04632	1,114	546
41	0.0094	363	(325,402)	0.0434	667	304
42	0.0094	363	(325,402)	0.0434	766	403
44	0.0148	572	(524,620)	0.04592	665	93
45	0.0058	224	(194,254)	0.04503	965	741
46	0.0088	340	(303,377)	0.04479	808	468
47	0.0041	158	(133,184)	0.04272	280	122
49	0.0015	58	(43,73)	0.04861	118	60
51	0.0233	901	(841,961)	0.0456	1,043	142
52	0.0056	217	(187,246)	0.04491	284	67
55	0.0061	236	(205,267)	0.04352	502	266
57	0.0019	73	(56,91)	0.04097	265	192
63	0.0233	901	(841,961)	0.0456	1,057	106
65	0.0199	769	(714, 825)	0.0454	771	2
71	0.0189	731	(677,785)	0.04578	1,049	318
74	0.0824	3,186	(3,073,3,299)	0.04529	3,710	524
75	0.0145	561	(513,608)	0.04481	725	164
76	0.0304	1,175	(1,107,1,244)	0.04571	1,842	667
97	0.0054	209	(180,238)	0.04477	476	267

A condition of fitting a Poisson process is that the conditions between different time periods must be the same. Otherwise, the main use of the Poisson process becomes descriptive and not prescriptive. Two formal hypotheses tests were conducted for each two digit work unit code level, one based on flying hours and the other based on sorties. These hypotheses tests determine whether the demand rates are the same or different for the 1993 and 1994 data sets used in this study. The results of these hypotheses tests are

included in Table 4-5 below. Detailed calculations for the hypotheses testing are included in Appendix F, starting on page F-27.

Table 4-5. Results of Poisson Process Hypotheses Testing

Two Digit Work Unit Code Level	Flying Hour Based Hypotheses Test	Result	Sortie Based Hypotheses Test	Result
11	$H_o: \lambda_{93} = \lambda_{94}$ $H_a: \lambda_{93} \neq \lambda_{94}$	Reject H_o	$H_o: \lambda_{93} = \lambda_{94}$ $H_a: \lambda_{93} \neq \lambda_{94}$	Reject H_o
12	" "	Reject H_o	" "	Reject H_o
13	" "	Reject H_o	" "	Reject H_o
14	" "	Reject H_o	" "	Reject H_o
23	" "	Reject H_o	" "	Reject H_o
24	" "	Reject H_o	" "	Reject H_o
41	" "	Reject H_o	" "	Reject H_o
42	" "	Reject H_o	" "	Reject H_o
44	" "	Reject H_o	" "	Reject H_o
45	" "	Reject H_o	" "	Reject H_o
46	" "	Reject H_o	" "	Reject H_o
47	" "	Reject H_o	" "	Reject H_o
49	" "	Reject H_o	" "	Reject H_o
51	" "	Reject H_o	" "	Reject H_o
52	" "	Reject H_o	" "	Reject H_o
55	" "	Reject H_o	" "	Reject H_o
57	" "	Reject H_o	" "	Reject H_o
63	" "	Reject H_o	" "	Reject H_o
65	" "	Accept H_o	" "	Accept H_o
71	" "	Reject H_o	" "	Reject H_o
74	" "	Reject H_o	" "	Reject H_o
75	" "	Reject H_o	" "	Reject H_o
76	" "	Reject H_o	" "	Reject H_o
97	$H_o: \lambda_{93} = \lambda_{94}$ $H_a: \lambda_{93} \neq \lambda_{94}$	Reject H_o	$H_o: \lambda_{93} = \lambda_{94}$ $H_a: \lambda_{93} \neq \lambda_{94}$	Reject H_o

The results shown in Table 4-5 indicate that the rate of demand or maintenance action occurrence changed between 1993 and 1994, which explains why only one of the two digit work unit levels, level 65, IFF, fell within the computed confidence interval. Level 65 was

also the only two digit work unit code level which accepted the null hypothesis indicating the demand rates were the same between 1993 and 1994. Based on the data used in this study, this hypothesis testing shows that under a fitted Poisson process, 1994 demands cannot be accurately predicted from 1993 demand rates at the work unit code level.

To analyze which phase of the methodology produces the best model or estimation technique at the work unit code level, the following section compares the residual values from obtained from multiple regression, Poisson regression, and fitting of a Poisson process.

Analysis/Comparison of Residuals

Table 4-6 on the next page compares the residuals obtained from the Poisson regression and Poisson Process calculations. The multiple regression residual values are not included in the comparison analysis because residual values were only calculated for 4 of the 24 two digit work unit code levels, due to the poor R^2 values. The average residual value for the Poisson regression analysis is 668.92 (16,054/24 = 668.92). The Poisson process (flying hour based) average residual is 309.5 (7,428/24 = 309.5), while the Poisson process (sortie based) average residual is 329.29 (7,903/24 = 329.29).

Based on the comparison analysis of the Poisson regression and Poisson process residual and overall average residual values, the Poisson process provides a better fit to the data than the Poisson regression technique. The four multiple regression residual values calculated are also large in comparison to the Poisson process residuals. Although the Poisson process does provide better residuals than multiple or Poisson regression, the expected number of 1994 maintenance actions calculated from the Poisson process were still significantly different from the actual 1994 values. Also, hypotheses testing under the fitted Poisson process indicates demand rates between 1993 and 1994 were different, which reduced the estimation capability of any Poisson process models. Thus, as observed

with multiple and Poisson regression, a Poisson process did not prove to be a good estimator of expected demands or maintenance actions at the work unit code level.

Table 4-6. Comparison of Residuals

Two-Digit Work Unit Code Level	Poisson Regression Residuals	Poisson Process Residuals (Flying Hour based)	Poisson Process Residuals (Sortie Based)
11	398	499	508
12	-123	149	156
13	1,827	146	209
14	908	729	742
23	1,746	792	836
24	861	530	546
41	399	293	304
42	399	392	403
44	373	75	93
45	512	736	741
46	415	459	468
47	-355	111	122
49	-355	58	60
51	743	109	142
52	45	61	67
55	301	255	266
57	212	187	192
63	705	123	106
65	504	-24	2
71	735	296	318
74	3,378	414	524
75	525	147	164
76	1,568	631	667
97	333	260	267

Summary

This chapter covered the results obtained from the three phases of the research methodology, which are multiple regression, Poisson regression, and a Poisson process. Current Air Force requirements computation programs use only flying hours to forecast demand. The intent of this study was to determine if a relationship exists between

demands, cumulative flying hours, and number of sorties at the work unit code level. Despite evaluating the data from three different angles, a significant relationship between demands/maintenance actions, cumulative flying hours, and number of sorties could not be found at the work unit code level. The next chapter presents the conclusions and recommendations of this research study.

V. Conclusions and Recommendations

Introduction

The purpose of this chapter is to present conclusions and recommendations obtained from the research. Initially, the specific problem, purpose of the study, and research questions will be presented. Following this initial discussion, the results, conclusions, and important management implications obtained for each research question will be discussed. Recommendations for follow-on research will then be presented. To conclude the chapter, a research summary will be provided.

Specific Problem

Current Air Force requirements computation systems, for example, D041 and REALM, forecast peacetime and MRSP reparable requirements based solely on a flying hour basis. The specific problem is to determine whether demands or maintenance actions of reparable spare parts are correlated to operational characteristics of the weapon system, specifically flying hours and sorties. Because current requirements models assume only a direct, linear relationship to the number of flying hours, demands/maintenance actions could be driven by other factors, or a combination of factors, to include flying hours and/or number of sorties.

Purpose of the Study

The primary purpose of this study is to determine whether or not a relationship exists between reparable spares demands/maintenance actions, flying hours, and number of sorties at the work unit code level. A secondary purpose is to develop models and decision rules based on the existing demands, flying hours, sortie relationship, which can be used to improve forecasting of reparable peacetime and MRSP spare requirements.

Research Questions

To evaluate the extent of correlation between demands/maintenance actions, flying hours, and number of sorties at the work unit code level, the following research questions are developed:

1. Is there a relationship between demands/maintenance actions, flying hours, and number of sorties at the work unit code level?

2. Can decision rules be established to forecast demands/maintenance actions based on a spares work unit code alone?

The results, conclusions, and management implications for each research question will now be presented.

Research Question One: Results, Conclusions, and Management Implications

The following section discusses the results from the multiple regression, Poisson regression, and Poisson process analyses used to answer research question one, "Is there a relationship between demands/maintenance actions, flying hours, and number of sorties at the work unit code level?" Conclusions and important Air Force management implications, which could be derived from these results, are also covered.

Results. The multiple regression, Poisson regression, and Poisson process results show that there is a limited relationship between demands/maintenance actions, flying hours, and number of sorties at the work unit code level. The low R^2 values obtained with multiple regression, the large deviance values obtained from Poisson regression, and the single occurrence of meeting the bounds of a calculated Poisson process confidence interval indicate the data used in this study do not support a relationship between demands/maintenance actions, flying hours, and number of sorties at the work unit code level. Also, a strong relationship between demands/maintenance actions, flying hours, and

number of sorties was not found at any two, three, or five digit work unit code level analyzed.

The answer to investigative question one, "Are demands or maintenance actions, and number of sorties correlated at the two digit level of specific work unit codes?", is similar to the answer for research question one. Although demands/maintenance actions were aggregated at the two digit work unit code level, to increase the number of points available for analysis, there was limited correlation obtained at the two digit work unit code level by using either multiple regression, Poisson regression, or fitting of a Poisson process.

As for investigative question two, "Do demands or maintenance actions, flying hours, and number of sorties show more, or less, correlation at the three, four, or five digit level of specific work unit codes, as compared to the two digit level?", the answer is that there is less correlation at the three, four, or five digit level of the work unit code in comparison to the two digit level. The correlation obtained at the two digit work unit code level is limited. However, by moving to lower, more defined, levels of the work unit code, the number of positive, regression points available for analysis decreases. This decrease is due to the number of zero values for demands against specific work unit codes increasing by moving to lower levels of the work unit code.

At the five digit work unit code level, a majority of the aircraft may not experience a demand/maintenance action for the specific five digit work unit code being analyzed. If the aircraft experiences no demands/maintenance actions for this five digit work unit code, the criterion variable, demands/maintenance actions, enters the regression with a value of zero. As the number of zero values increases in the regression, the extent of correlation decreases.

Poisson regression analysis also exhibits a similar lack of correlation based on the large deviance values. Any models subsequently developed from either the multiple or

Poisson regression analysis exhibit poor predictive capability when used to estimate demands or maintenance actions based on a 1994 validation data set. The large residual values obtained from residual analysis on the multiple and Poisson regression models indicate the models perform poorly in estimating expected numbers of demands/ maintenance actions.

Results obtained by fitting a Poisson process were similar to the results obtained from multiple and Poisson regression. The demand estimates and confidence intervals calculated with the Poisson process for the 1994 validation data set were normally much lower than the actual number of 1994 demands experienced. Also, only 1 of 24 two digit work unit code levels evaluated fell within the calculated confidence interval.

Also, by fitting a Poisson process to various data sets, similar conditions must be maintained between data sets. In other words, the lambda values, or rates of occurrence, must stay relatively constant between time periods. However, the lambda values calculated for the 1993 data set were much lower than the lambda values for 1994. Thus, the demand estimates and confidence intervals calculated from the 1993 lambda values were lower than the actual number of 1994 demands.

The Poisson process analysis further exhibits that the erratic nature of demands makes forecasting future demands at the work unit code level a difficult process. The calculated Poisson process work unit code level demand/maintenance action estimates, which are based on flying hours and sorties from past demands, are poor estimators of future demands/maintenance actions.

Conclusions. A conclusion is reached that aligning demands/maintenance actions with their underlying failure modes remains a complicated issue, despite analysis at the work unit code level. However, this research is unique in that it targets reparable demand forecasting at the work unit code level. Another conclusion the research supports is the limited correlation obtained across the F-15C weapon system at the work unit code level.

This limited correlation between demands/maintenance actions, flying hours, and number of sorties at the work unit code level supports previous demand forecasting research in that a significant relationship could not be determined to accurately predict reparable demands.

Management Implications. The current Air Force requirements computation systems calculate reparable requirements based solely on flying hours. However, some reparable spares may not fail on a strictly flying hour basis. Thus, based on the current Air Force systems, some flying hour driven spares are stocked with accurate quantities, while other non-flying hour driven spares are either over or under stocked. This study attempted to identify a relationship between demands, flying hours, and number of sorties at the work unit code level and align demands/maintenance actions with accurate spares requirements.

Despite the limited correlation obtained at the work unit code level, this research is important and has significant Air Force management implications. First, further research in the area of reparable demand forecasting is still required because an accurate, reliable relationship between demands, flying hours, and sorties could not be determined in this study. Second, this research supports the multitude of previous demand forecasting research in that a relationship was not found between demands, flying hours, and sorties. However, this study expands upon this previous research and uses greater insight by delving into the correlation between weapon system demands/maintenance actions, flying hours, and number of sorties at the work unit code level. This study is also a unique, first attempt at obtaining a correlation between demands, or maintenance actions, and spares requirements at the work unit code level. Third, the study uses large, REMIS maintenance and sortie data sets for limited time periods from 1993 and 1994. In spite of the short time periods, the combined size of these data sets is still nearly 100,000 maintenance and sortie images. Although these data sets are a large, representative

sample of REMIS data, a significant correlation could not be found between demands/maintenance actions, cumulative flying hours, and number of sorties at the work unit code level. In other words, this study was not small in scale and used one of the best available sources of data. Finally, the most important management implication is the benefit which could be gained by determining a demand, flying hour, sortie relationship at the work unit code level, particularly the five digit level. In determining a demand, flying hour, sortie relationship, the specific five digit work unit code level could eventually be matched to a national stock number. The significant benefit gained by the Air Force is that maintenance and supply technicians could use this five digit work unit code/national stock number match to predict accurate, on-hand quantities of reparable spares. By knowing the expected number of maintenance actions, the required amount of reparable spares could be maintained in peacetime inventories or configured in MRSPs. Thus, demand forecasting research at the work unit level is worthwhile and could possibly derive significant financial and operational benefits, if properly researched, developed, and deployed.

Research Question Two: Results, Conclusions, and Management Implications

This section discusses the results obtained to answer research question two, "Can decision rules be established to forecast demands/maintenance actions based on a spares work unit code alone?" Conclusions and important Air Force management implications are also covered.

Results. Based on the lack of fit obtained from the multiple or Poisson regression models and the Poisson process estimation techniques, decision rules cannot be established based solely on a spares work unit code. The optimal answer to research question two would have been to develop regression or estimation models for specific work unit codes,

which would require inputs of flying hour and sortie profiles to calculate the expected number of demands or maintenance actions. However, the models obtained from this study show limited correlation and would not be suitable for establishment of work unit code decision rules.

Conclusions. A primary conclusion is that the limited results obtained under research question one prohibit the development of work unit code decision rules, which could be used to estimate demands or maintenance actions based on operational factors of a weapon system. However, a secondary conclusion is that the limited number of demands/maintenance actions, particularly at the five digit work unit code level, did portray the erratic, uncertain nature of demands that is a common characteristic of reparable spares. The current DoD situation of tight budgets and slim force structures require accurate, reliable reparable inventories to compensate for the inherent problem of demand uncertainty. Accurate work unit code decision rules could possibly assist in irradiating this troublesome problem of erratic, uncertain demand.

Management Implications. Development of work unit code decision rules could have significant management implications in managing peacetime reparable inventories and configuring MRSPs. A major issue is that the work unit code decision rules must be established from analytical models which exhibit a significant amount of correlation. In other words, the operational factors used to generate the models must provide accurate predictive capability (low residuals) on the expected number versus actual number of demands/maintenance actions. However, the problem is determining the operational factors of the weapon system which drive the demands/maintenance actions. In this study, only the operational factors of flying hours and sorties were analyzed, which produced poor estimation models.

Accurate reparable inventories could be maintained to support specific peacetime flying profiles by aligning demands with the operational factors which cause the demands

and establishing work unit code decision rules. In the current DoD environment of Depot Level Reparables (DLRs), an operational wing is very interested in the quantity of reparable spares used because, instead of the Air Force stock fund paying for these reparables, the operational wing now pays for reparables out of operations and maintenance (O&M) funding. Reliable work unit code decision rules could ensure only required reparable inventories are maintained, while also saving operational wing O&M funding.

The work unit code decision rules could also significantly enhance MRSP configurations. If a given wartime scenario is known, the operational factors which drive the estimation models could be determined. These operational factors can be used to compute the number of expected demands/maintenance actions from the specific work unit code decision rules. The number of spares required to support the wartime scenario could then be determined by cross referencing the work unit code to the national stock number. By only deploying the required number of MRSP spares, the Air Force saves money and conserves vital mobility airlift capability, which can quickly become a limiting logistical resource given the areas of responsibility (AORs) of our most recent conflicts/wars. The recommendations for follow-on research are included in the next section.

Recommendations for Follow-on Research

There are two primary factors which constrained the analysis conducted in this study. These factors are the limited amount of data and the limited number of predictor variables available for regression/estimation analysis. Therefore, we make the following three recommendations for follow-on research. First, evaluate the demands/maintenance action, flying hour, sortie relationship at the work unit code level with a much larger data set. Second, conduct an exploratory study to determine what factors drive specific spares

to fail. Finally, using the same technique of this study, analyze a different weapon system and compare the results. Each of these recommendations will now be discussed.

The data sets used in this study were limited to eight months for 1993 and five months for 1994. Analysis at the work unit code level should be evaluated with a CAMS or REMIS data set containing at least two years worth of data. A larger data set is suggested because the current D041 system uses eight quarters, or two years, of data to compute Air Force reparable requirements. By using a larger data set, an in-depth evaluation at the five digit work unit code level could be performed. Due to the lack of specific five digit work unit code occurrences, this study aggregated work unit codes at the two, three, four, and five digit level to obtain enough points for meaningful regression analysis. A larger data set would provide sufficient occurrences of five digit work unit codes to allow for regression or Poisson process analysis at the five digit work unit code level. Also, any subsequent decision rules would estimate the number of expected five digit work unit code occurrences. This study would have only provided an estimate of the number of two digit work unit code level occurrences, if significant correlation could have been obtained.

Along with a larger data set, an exploratory study also needs to be conducted to determine what factors cause failures of specific spares. Based on the results presented in Chapter Four, the limited correlation between demands/maintenance actions, flying hours, and number of sorties at the work unit code level show that demands/maintenance actions are possibly driven by factors other than flying hours and number of sorties. The exploratory study needs to evaluate other operational factors, such as engine cycles, takeoffs/landings, and so on, to determine exactly which factors drive failures of reparable spares. If operational factors can be determined, reliable regression or estimation models can be developed based on the operational factors that drive generation of demands or maintenance actions for particular spares.

The results obtained in this study should be considered as only a single data point because similar studies have not been performed at the work unit code level. A follow-on study could be performed against another fighter weapon system, such as an F-16, or against a transport weapon system, such as a C-5 or C-141. The operational profiles of the F-15C analyzed in this study could have contributed to the lack of correlation obtained by analyzing the demands, flying hour, sortie relationship at the work unit code level. However, a comparable study performed against a transport aircraft, or another fighter aircraft, could produce similar or contradictory results. Research at the work unit code level is still in the preliminary stages and should not be abandoned after analysis of only a single weapon system, the F-15C.

This research study was extremely involved, required several attempts to obtain the phased methodology, and also required a significant amount of data manipulation. Nevertheless, the research is an initial study and has possibly opened the door to a significant amount of follow-on research at the work unit code level. Follow-on researchers should first of all obtain a reliable, "clean," data set to use for analysis. In referring to a "clean" data set, researchers should possibly obtain a reliable data set directly from CAMS, instead of attempting to use a REMIS data base that receives downloads from CAMS. By focusing on only CAMS data, the analysis may be limited to only a few bases instead of the worldwide REMIS sample used in this study. However, accurate downloads of a small amount of CAMS data may provide more concrete results than a large amount of questionable REMIS data. The bottom line to any research study is that the results will only be as good as the data which is analyzed.

Second, researchers should possibly consider a time between maintenance actions study, if sufficient occurrences of specific five digit work unit codes are present within the data. This study aggregated work unit codes and did not consider the time between maintenance actions. However, by focusing on the time between occurrences of the same

maintenance action, a researcher would obtain a more accurate representation of the flying hours, number of sorties, or other operational characteristics that actually transpire between occurrences of the same work unit code.

Third, follow-on researchers should thoroughly research all available statistical techniques in attempting to obtain a best "fit" to the data. Although this study used three techniques, multiple regression, Poisson regression, and fitting of a Poisson process, the use of REMIS data covering only F-15C worldwide flying profiles may or may not have been a contributing factor to the lack of correlation. CAMS or REMIS data on another weapon system, analyzed with a the same or a different statistical process, may provide entirely different results to those obtained in this study.

Finally, researchers must focus on developing some form of decision mechanism, which addresses the problem, and is suitable for use in the operational Air Force. The work unit code decision rules, which were an objective of this study, were not successfully generated. However, if these decision rules could have been developed, they would have required only simple inputs of flying hours or number of sorties to generate the expected number of demands/maintenance actions. Decision mechanisms developed from a research study must be applicable to the problem addressed and straight-forward enough to be used by those who need them the most.

By using a larger data set, obtaining "true" operational factors which drive failures, and analyzing a different fighter or transport weapon system, reliable models could be developed to determine the expected number of demands/maintenance actions at the five digit work unit code level. The establishment of a five digit work unit code level cross reference to the national stock number would then determine required inventory levels for reparable spares. However, the primary driving factor is determining what factors cause specific reparable spares to fail.

Research Summary

Current Air Force demand forecasting systems, D041 and REALM, assume reparable demand is solely flying hour driven. This research study presents the problem of determining whether demands/maintenance actions of aircraft reparable spares are correlated to flying hours and number of sorties at the work unit code level. A literature review examining the relationship between reparable failures and/or predictor variables is provided, to include a discussion on reparable spares management in the civilian sector.

The research focuses on worldwide F-15C REMIS data from May to December 1993 and February to June 1994. The data sets cover only a specified timeframe, however, nearly 100,000 F-15C sortie and maintenance images are analyzed. A three phase methodology is used to determine whether or not a relationship exists between demands/maintenance actions, flying hours, and number of sorties at the work unit code level. Phase One of the methodology uses multiple linear regression, while Phase Two employs Poisson regression. The third and final phase fits a Poisson process to the data. Despite evaluating the data by three different statistical techniques, a conclusion is reached that significant correlation could not be obtained between demands/maintenance actions, flying hours, and number of sorties at the work unit code level. The lack of correlation also prohibits development of work unit code decision rules, which could be used to estimate expected numbers of demands/maintenance actions given a specified flying hour and sortie profile. Recommendations for follow-on research are also provided.

This research study supports previous demand forecasting by not determining an accurate relationship between demands, flying hours, and sorties. However, by evaluating the relationship at the work unit code level, the study takes a leap forward into uncharted territory concerning reparable demand forecasting. Further research at the work unit code level may provide the elusive answer required to resolve the issue of matching erratic, uncertain, reparable demands with accurate spares requirements. By allocating "accurate

quantities of the right item, to the right place, at the right time," the Air Force can enhance peacetime operational readiness, while significantly improving wartime combat capability.

Appendix A: Work Unit Code Breakdown

A work unit code is a five digit alpha numeric code used by Air Force maintenance personnel to track specific maintenance actions at the system level and first/second level of assembly for major aircraft systems. Thirty-three separate levels may be identified with a single five-digit work unit code.

Construction of the work unit code designates the first two numeric characters in the sequence followed by three zeros as the system designator. The first level of assembly is designated by the first two numeric characters plus the third alpha character followed by two zeros. Two numeric characters, an alpha character followed by another alpha character or a numeric character and a zero designates the second level of assembly. Finally, the third level of assembly uses an alpha or a numeric character in the fifth character position. The number "99" used in the fourth and fifth positions indicate Not Otherwise Coded (NOC). This code provides a work unit code for components that do not have specific codes assigned. For example:

33000 - SYSTEM DESIGNATOR

33A00 - FIRST LEVEL OF ASSEMBLY

33AA0 - SECOND LEVEL OF ASSEMBLY

33AAA - THIRD LEVEL OF ASSEMBLY

33A99 - NOC

(Reference: MIL-M-38769C (USAF)

Table A-1 on the next page lists the two digit work unit code levels and their corresponding F-15C aircraft systems/components.

Table A-1. Two Digit Work Unit Code Level/System or Component Comparison

Two Digit Work Unit Code Level	F-15C System/Component
11	Airframe
12	Cockpit and Fuselage Compartments
13	Landing Gear
14	Flight Controls
23	Turbofan Power Plant
24	Auxiliary Power Plant
41	Air Conditioning, Pressurization, and Surface Ice Control
42	Electrical Power Supply
44	Lighting System
45	Hydraulic and Pneumatic Power Supply
46	Fuel System
47	Oxygen System
49	Miscellaneous Utilities
51	Instruments
52	Autopilot
55	Malfunction Analysis and Recording Equipment
57	Integrated Guidance and Flight Control
63	UHF Communication
65	IFF
71	Radio Navigation
74	Fire Control
75	Weapons Delivery
76	Electronic Countermeasures
97	Explosive Devices and Components Miscellaneous Series Aircraft Explosive Devices

Appendix B: Statistical Analysis System (SAS) Routines

SAS Routine Used to Sort and Merge the 1993 Analysis Data Set

```
*** READING MAINTENANCE ACTION DATA INTO DATA FILE 'temp' ***
options linesize=78;
data temp missover;
  infile maintain;
      input tail $ 1-4 eventid $ 5-13 wuc $ 14-18
          at $ 19 wd $ 20 hm $ 21-23
          beg 26-29 nos $ 30-32 date $ 33-37
          sdate $ 38-42 sbeg 43-46 snos $ 47-49
          slen 51-53 smis $ 54-57 ck 59
          nsort 61-62 sran $ 63-66;

*** READING SORTIE DATA INTO DATA FILE 'temp1' ***
data temp1 missover;
  infile sortie;
      input tail $ 1-4 sdate $ 5-9 snos $ 10-12
          smis $ 13-16 sbeg 17-20 slen 22-24
          sran $ 25-28 nsort 30-31;

*** DELETING 160 AIRCRAFT FROM 1993 SORTIE DATA WHICH HAVE NO
    CORRESPONDING MAINTENANCE ACTION DATA ***
   if tail eq '2012' or tail eq '2013' or tail eq '2014' then delete;
   if tail eq '2015' or tail eq '2016' or tail eq '2017' then delete;
   if tail eq '2018' or tail eq '2019' or tail eq '2021' then delete;
   if tail eq '2022' or tail eq '2023' or tail eq '2024' then delete;
   if tail eq '2025' or tail eq '2026' or tail eq '2027' then delete;
   if tail eq '2028' or tail eq '2029' or tail eq '2030' then delete;
   if tail eq '2031' or tail eq '2032' or tail eq '2033' then delete;
   if tail eq '2034' or tail eq '2035' or tail eq '2036' then delete;
   if tail eq '2037' or tail eq '2038' or tail eq '3010' then delete;
   if tail eq '3011' or tail eq '3012' or tail eq '3013' then delete;
   if tail eq '3014' or tail eq '3015' or tail eq '3016' then delete;
   if tail eq '3017' or tail eq '3018' or tail eq '3019' then delete;
   if tail eq '3020' or tail eq '3022' or tail eq '3023' then delete;
   if tail eq '3024' or tail eq '3025' or tail eq '3026' then delete;
   if tail eq '3027' or tail eq '3028' or tail eq '3029' then delete;
   if tail eq '3030' or tail eq '3031' or tail eq '3032' then delete;
   if tail eq '3033' or tail eq '3034' or tail eq '3035' then delete;
   if tail eq '3036' or tail eq '3037' or tail eq '3038' then delete;
   if tail eq '3039' or tail eq '3040' or tail eq '3041' then delete;
```

```
if tail eq '3042' or tail eq '3043' or tail eq '4001' then delete;
if tail eq '4002' or tail eq '4003' or tail eq '4004' then delete;
if tail eq '4005' or tail eq '4006' or tail eq '4007' then delete;
if tail eq '4008' or tail eq '4009' or tail eq '4010' then delete;
if tail eq '4011' or tail eq '4012' or tail eq '4013' then delete;
if tail eq '4014' or tail eq '4015' or tail eq '4016' then delete;
if tail eq '4017' or tail eq '4018' or tail eq '4019' then delete;
if tail eq '4020' or tail eq '4021' or tail eq '4022' then delete;
if tail eq '4023' or tail eq '4024' or tail eq '4025' then delete;
if tail eq '4026' or tail eq '4027' or tail eq '4028' then delete;
if tail eq '4030' or tail eq '4031' or tail eq '5093' then delete;
if tail eq '5094' or tail eq '5095' or tail eq '5096' then delete;
if tail eq '5097' or tail eq '5098' or tail eq '5099' then delete;
if tail eq '5100' or tail eq '5101' or tail eq '5102' then delete;
if tail eq '5103' or tail eq '5104' or tail eq '5105' then delete;
if tail eq '5106' or tail eq '5107' or tail eq '5108' then delete;
if tail eq '5110' or tail eq '5111' or tail eq '5112' then delete;
if tail eq '5113' or tail eq '5114' or tail eq '5115' then delete;
if tail eq '5117' or tail eq '5118' or tail eq '5119' then delete;
if tail eq '5120' or tail eq '5121' or tail eq '5122' then delete;
if tail eq '5123' or tail eq '5124' or tail eq '5125' then delete;
if tail eq '5126' or tail eq '5127' or tail eq '5128' then delete;
if tail eq '6143' or tail eq '6144' or tail eq '6145' then delete;
if tail eq '6146' or tail eq '6147' or tail eq '6148' then delete;
if tail eq '6149' or tail eq '6150' or tail eq '6151' then delete;
if tail eq '6152' or tail eq '6154' or tail eq '6155' then delete;
if tail eq '6156' or tail eq '6157' or tail eq '6158' then delete;
if tail eq '6159' or tail eq '6160' or tail eq '6161' then delete;
if tail eq '6162' or tail eq '6163' or tail eq '6164' then delete;
if tail eq '6165' or tail eq '6166' or tail eq '6167' then delete;
if tail eq '6168' or tail eq '6169' or tail eq '6170' then delete;
if tail eq '6171' or tail eq '6172' or tail eq '6173' then delete;
if tail eq '6174' or tail eq '6175' or tail eq '6176' then delete;
if tail eq '6177' or tail eq '6178' or tail eq '6179' then delete;
if tail eq '6180' then delete;

*** SORTING temp DATA FILE BY TAIL NUMBER, SORTIE DATE, AND
    NUMBER OF SORTIES ***
proc sort data=temp;
  by tail sdate nsort;
    run;
```

```
*** SORTING temp1 DATA FILE BY TAIL NUMBER, SORTIE DATE, AND
    NUMBER OF SORTIES ***
proc sort data=temp1;
   by tail sdate nsort;
     run;

*** MERGING temp AND temp1 DATA FILES INTO DATA FILE 'master1' BY
    MATCHING TAIL NUMBER, SORTIE DATE, AND NUMBER OF SORTIES ***
data master1;
   merge temp temp1;
   by tail sdate nsort;
   run;

*** SORTING master1 DATA FILE BY TAIL NUMBER AND SORTIE DATE ***
proc sort data=master1;
   by tail sdate;
   run;

*** PRINTING master1 DATA FILE ***
proc print data=master1;
   var tail eventid wuc sdate snos slen smis nsort sran;
   run;
```

SAS Routine Used to Sort and Merge the 1994 Validation Data Set

```
*** READING MAINTENANCE ACTION DATA INTO DATA FILE 'temp' ***
options linesize=78;
data temp missover;
  infile dremism;
       input tail $ 1-4 eventid $ 5-13 wuc $ 14-18
       at $ 19 wd $ 20 hm $ 21-23 up 24-25 beg 26-29
       nos $ 30-32 s $ 33 date $ 34-38 sdate $ 39-43
       sbeg 44-47 snos $ 48-50 slen 51-54 smis $ 55-58
       ck 59-60 p $ 61 nsorts 62-64 from $ 65-68;
if ck eq '99' then delete;

*** READING SORTIE DATA INTO DATA FILE 'temp1' ***
data temp1 missover;
  infile dremiss;
       input tail $ 1-4 sdate $ 5-9 snos $ 10-12
       smis $ 13-16 sbeg 17-20 slen 21-24 nsorts 25-27
       loc 28-29 from $ 30-33;

*** SORTING temp DATA FILE BY TAIL NUMBER, SORTIE DATE, BEGINNING
    TIME OF SORTIE, AND SORTIE LENGTH ***
proc sort data=temp;
  by tail sdate sbeg slen;
  run;

*** SORTING temp1 DATA FILE BY TAIL NUMBER, SORTIE DATE, BEGINNING
    TIME OF SORTIE, AND SORTIE LENGTH ***
proc sort data=temp1;
  by tail sdate sbeg slen;
  run;

*** MERGING temp AND temp1 DATA FILES INTO DATA FILE 'master94' BY
    MATCHING TAIL NUMBER, SORTIE DATE, BEGINNING TIME OF SORTIE,
    AND SORTIE LENGTH ***
data master94;
  merge temp temp1;
  by tail sdate sbeg slen;
  run;

*** SORTING master94 DATA FILE BY TAIL NUMBER AND SORTIE DATE ***
proc sort data=master94;
  by tail sdate;
  run;
```

```
*** PRINTING master94 DATA FILE ***
proc print data=master94;
  var tail sdate wuc slen from;
  run;
```

Appendix C: FORTRAN Programs and 1993/1994 Data Output Samples

FORTRAN Program Used for 1993 Analysis Data

PROGRAM CALCULATES NUMBER OF WORK UNIT CODE OCCURRENCES, CUMULATIVE FLYING HOURS, AND NUMBER OF SORTIES FOR EACH TAIL NUMBER IN THE 1993 DATA SET. CHARACTERS IN **BOLD TYPE** CAN BE VARIED TO CALCULATE NUMBER OF WORK UNIT CODE OCCURRENCES, CUMULATIVE FLYING HOURS, AND NUMBER OF SORTIES AT DIFFERENT LEVELS OF THE WORK UNIT CODE.

```
PROGRAM MAIN

*** INITIALIZING VARIABLES ***

    REAL*8 SLEN
    INTEGER*4 NOBS, NTAIL, NDATE, NSNOS, NSORT
    CHARACTER*4 SMIS
    CHARACTER*5 SRAN
    CHARACTER*9 EVENTID
    CHARACTER*5 WUC
    CHARACTER*5 WUCINT
    INTEGER*4 CURTAL
    REAL*8 HOURS
    INTEGER*4 NLINE, ISORT, NHITS
    CHARACTER*7 TRASH
    REAL*4 HOURS2, HOURSORT
    INTEGER*4 ISORT2

*** OPENING FILES ***

    OPEN(1,FILE='USER2:[SKEPHART.GETDATA]MERGE2.LIS',STATUS='OLD')
    OPEN(2,FILE='USER2:[SKEPHART.GETDATA.DATA] 11A99.MULTI',
   1   STATUS='NEW')

*** FORMATS ***

1001 FORMAT(I6,3X,I4,3X,A9,3X,A5,3X,I5,3X,I3,3X,F5.1,3X,
   1    A4,3X,I4,3X,A5)
1002 FORMAT(A7)
2001 FORMAT(' ',I4,3X,A5,3X,I4,3X,F8.1,3X,I5,3X,F10.2,3X,I8,F10.2)
```

```
*** SETTING VARIABLES TO 0 AND IDENTIFYING WORK UNIT CODE ***

      CURTAL = 0
      HOURS = 0.0
      WUCINT = '11A99'
      NLINE = 0
      ISORT = 0
      NHITS = 0
100   CONTINUE

*** INCREMENTING DATA LINES AND DISCARDING PAGE HEADERS ***

      NLINE = NLINE + 1
      IF (NLINE .EQ. 62) THEN
        NLINE = 1
      ENDIF

      IF (NLINE .LT. 7) THEN
        READ(1,1002)TRASH
        GO TO 100
      ENDIF

*** READING DATA IMAGES ***

      READ(1,1001,END=900) NOBS, NTAIL, EVENTID, WUC, NDATE, NSNOS,
     1     SLEN, SMIS, NSORT, SRAN

*** ESTABLISHING TAIL NUMBER OF THE AIRCRAFT ***

      IF (CURTAL .EQ. 0) THEN
        CURTAL = NTAIL
      ENDIF

*** ACCUMULATING FLYING HOURS, SORTIES, AND NUMBER OF WORK
    UNIT  CODE HITS FOR EACH TAIL NUMBER ***

      IF (NTAIL .EQ. CURTAL) THEN
        HOURS = HOURS + SLEN
        ISORT = ISORT + 1
        IF (WUC .EQ. WUCINT) THEN
          NHITS = NHITS + 1
        ENDIF
        GO TO 100
      ENDIF
```

```
*** CALCULATING SQUARED AND INTERACTION PARAMETERS ***

    HOURS2 = HOURS * HOURS
    ISORT2 = ISORT * ISORT
    HOURSORT = HOURS * REAL(ISORT)

*** WRITING RECORDS TO FILE ***

    WRITE(2,2001) CURTAL, WUCINT, NHITS, HOURS, ISORT,
   1          HOURS2, ISORT2, HOURSORT

*** RESETTING VARIABLES ***

    CURTAL = NTAIL
    HOURS = SLEN
    ISORT = 1
    NHITS = 0
    IF (WUC .EQ. WUCINT) THEN
      NHITS = 1
    ENDIF
    GO TO 100
900 CONTINUE

*** CLOSING DATA FILES AND TERMINATING PROGRAM ***

    CLOSE(1)
    CLOSE(2)

    STOP
    END
```

FORTRAN Program Used for 1994 Validation Data

PROGRAM CALCULATES NUMBER OF WORK UNIT CODE OCCURRENCES, CUMULATIVE FLYING HOURS, AND NUMBER OF SORTIES FOR EACH TAIL NUMBER IN THE 1994 DATA SET. CHARACTERS IN **BOLD TYPE** CAN BE VARIED TO CALCULATE NUMBER OF WORK UNIT CODE OCCURRENCES, CUMULATIVE FLYING HOURS, AND NUMBER OF SORTIES AT DIFFERENT LEVELS OF THE WORK UNIT CODE.

```
PROGRAM VALID
*** INITIALIZING VARIABLES ***

    REAL*8 SLEN
    INTEGER*4 NOBS, NTAIL, NDATE
    CHARACTER*5 SRAN
    CHARACTER*2 WUC
    CHARACTER*2 WUCINT
    INTEGER*4 CURTAL
    REAL*8 HOURS
    INTEGER*4 NLINE, ISORT, NHITS
    CHARACTER*7 TRASH
    REAL*4 HOURS2, HOURSORT
    INTEGER*4 ISORT2

*** OPENING FILES ***

OPEN(1,FILE='USER2:[SKEPHART.VALDATA]1994MAINT.LIS',STATUS='OLD')
OPEN(2,FILE='USER2:[SKEPHART.VALDATA.DATA]11.VAL',
1   STATUS='NEW')

*** FORMATS ***

1001  FORMAT(T15,I6,T25,I4,T33,I5,T42,A2,T50,F5.1,T59,A5)
1002  FORMAT(A7)
2001  FORMAT(' ',I4,3X,A2,6X,I4,3X,F8.1,3X,I5,3X,F10.2,3X,I8,F10.2)

*** SETTING VARIABLES TO 0 AND IDENTIFYING WORK UNIT CODE ***

    CURTAL = 0
    HOURS = 0.0
    WUCINT = '11'
    NLINE = 0
    ISORT = 0
```

```
      NHITS = 0
  100 CONTINUE

*** INCREMENTING DATA LINES AND DISCARDING PAGE HEADERS ***

      NLINE = NLINE + 1
      IF (NLINE .EQ. 62) THEN
        NLINE = 1
      ENDIF

      IF (NLINE .LT. 7) THEN
        READ(1,1002)TRASH
        GO TO 100
      ENDIF

*** READING DATA IMAGES ***

      READ(1,1001,END=900) NOBS, NTAIL, NDATE, WUC, SLEN, SRAN

*** ESTABLISHING TAIL NUMBER OF THE AIRCRAFT ***

      IF (CURTAL .EQ. 0) THEN
        CURTAL = NTAIL
      ENDIF

*** ACCUMULATING FLYING HOURS, SORTIES, AND NUMBER OF WORK
    UNIT  CODE HITS FOR EACH TAIL NUMBER ***

      IF (NTAIL .EQ. CURTAL) THEN
        HOURS = HOURS + SLEN
        ISORT = ISORT + 1
        IF (WUC .EQ. WUCINT) THEN
          NHITS = NHITS + 1
        ENDIF
        GO TO 100
      ENDIF

*** CALCULATING SQUARED AND INTERACTION PARAMETERS ***

      HOURS2 = HOURS * HOURS
      ISORT2 = ISORT * ISORT
      HOURSORT = HOURS * REAL(ISORT)
```

```
*** WRITING RECORDS TO FILE ***

    WRITE(2,2001) CURTAL, WUCINT, NHITS, HOURS, ISORT,
   1          HOURS2, ISORT2, HOURSORT

*** RESETTING VARIABLES ***

    CURTAL = NTAIL
    HOURS = SLEN
    ISORT = 1
    NHITS = 0
    IF (WUC .EQ. WUCINT) THEN
      NHITS = 1
    ENDIF
    GO TO 100
900   CONTINUE

*** CLOSING DATA FILES AND TERMINATING PROGRAM ***

    CLOSE(1)
    CLOSE(2)

    STOP
    END
```

Table C-1. 1993 FORTRAN Program Data Output Sample

TAIL	WUC	DMDS	CUMFH	NSORT	CUMFH2	NSORT2	FHNSORT
2	13	1	227.7	141	51847.29	19881	32105.7
3	13	3	234.4	93	54943.36	8649	21799.2
4	13	4	72	51	5184	2601	3672
5	13	6	187.1	139	35006.41	19321	26006.9
6	13	8	182.4	160	33269.76	25600	29184
9	13	4	288.1	165	83001.61	27225	47536.5
10	13	10	163.8	89	26830.44	7921	14578.2
11	13	2	225.1	117	50670.01	13689	26336.7
12	13	10	444	213	197136	45369	94572
13	13	5	190	149	36100	22201	28310
14	13	12	205	161	42025	25921	33005
15	13	9	163.6	134	26764.96	17956	21922.4
16	13	5	136.6	107	18659.56	11449	14616.2
18	13	0	62.5	36	3906.25	1296	2250
19	13	4	163.7	127	26797.69	16129	20789.9
20	13	2	140.6	96	19768.36	9216	13497.6
22	13	4	398.2	134	158563.2	17956	53358.8
24	13	4	70.9	47	5026.81	2209	3332.3
26	13	11	221	144	48841	20736	31824
27	13	6	201.4	127	40561.96	16129	25577.8
28	13	1	347.3	126	120617.3	15876	43759.8
29	13	5	223.3	138	49862.89	19044	30815.4
30	13	5	140.1	116	19628.01	13456	16251.6
31	13	4	413.4	127	170899.6	16129	52501.8
33	13	4	117.1	101	13712.41	10201	11827.1
34	13	2	155.8	142	24273.64	20164	22123.6
35	13	2	173.5	99	30102.25	9801	17176.5
38	13	2	224.1	144	50220.81	20736	32270.4
39	13	5	147.3	91	21697.29	8281	13404.3
40	13	8	151.3	132	22891.69	17424	19971.6
41	13	3	18.4	15	338.56	225	276
43	13	4	151.4	139	22921.96	19321	21044.6
44	13	2	150.4	140	22620.16	19600	21056
45	13	7	165.9	147	27522.81	21609	24387.3
46	13	4	159.8	98	25536.04	9604	15660.4
47	13	5	215.6	133	46483.36	17689	28674.8
48	13	7	161.3	99	26017.69	9801	15968.7
49	13	4	105.4	104	11109.16	10816	10961.6
50	13	1	116.4	73	13548.96	5329	8497.2
51	13	3	209.6	136	43932.16	18496	28505.6
53	13	1	168	118	28224	13924	19824

54	13	6	210.8	148	44436.64	21904	31198.4
55	13	15	248.9	174	61951.21	30276	43308.6
57	13	8	139.6	87	19488.16	7569	12145.2
58	13	8	346.2	252	119854.4	63504	87242.4
60	13	13	193.6	157	37480.96	24649	30395.2
61	13	9	173.2	123	29998.24	15129	21303.6
1020	13	2	223.4	139	49907.56	19321	31052.6
1021	13	1	92	52	8464	2704	4784
1022	13	5	164.3	133	26994.49	17689	21851.9
1023	13	1	508.9	176	258979.2	30976	89566.4
1024	13	5	166.8	133	27822.24	17689	22184.4
1025	13	5	189.3	139	35834.49	19321	26312.7
1026	13	5	198.6	144	39441.96	20736	28598.4
1027	13	9	143.3	108	20534.89	11664	15476.4
1028	13	7	175.1	143	30660.01	20449	25039.3
1029	13	7	189.7	154	35986.09	23716	29213.8
1030	13	1	160.7	127	25824.49	16129	20408.9
1031	13	8	240.3	183	57744.09	33489	43974.9
1032	13	3	590.4	214	348572.2	45796	126345.6
1033	13	2	513.7	181	263887.7	32761	92979.7
1034	13	3	174	134	30276	17956	23316
1035	13	4	173.4	138	30067.56	19044	23929.2
1036	13	5	382.8	124	146535.8	15376	47467.2
1037	13	5	540.6	201	292248.4	40401	108660.6
1038	13	9	231.7	182	53684.89	33124	42169.4
1039	13	6	203.2	158	41290.24	24964	32105.6
1040	13	7	189.3	149	35834.49	22201	28205.7
1041	13	11	232.3	177	53963.29	31329	41117.1
1042	13	8	220.4	155	48576.16	24025	34162
1043	13	0	59.1	29	3492.81	841	1713.9
1044	13	2	183.6	131	33708.96	17161	24051.6
1045	13	6	179	137	32041	18769	24523
1046	13	13	176.4	137	31116.96	18769	24166.8
1047	13	9	193.7	126	37519.69	15876	24406.2
1048	13	9	223.1	168	49773.61	28224	37480.8
1050	13	5	161.1	123	25953.21	15129	19815.3
1051	13	6	181	141	32761	19881	25521
1053	13	8	122.5	113	15006.25	12769	13842.5
1054	13	0	78.8	50	6209.44	2500	3940
1055	13	3	151	142	22801	20164	21442
1061	13	7	259.8	170	67496.04	28900	44166
1062	13	3	123.8	100	15326.44	10000	12380
1063	13	6	202.8	157	41127.84	24649	31839.6
1064	13	10	149.1	118	22230.81	13924	17593.8

1065	13	14	251.5	191	63252.25	36481	48036.5
2008	13	6	135.9	108	18468.81	11664	14677.2
2009	13	6	198.8	152	39521.44	23104	30217.6
2010	13	8	226.4	164	51256.96	26896	37129.6
2011	13	1	165.5	128	27390.25	16384	21184
2044	13	14	178.2	141	31755.24	19881	25126.2
2045	13	1	17.2	13	295.84	169	223.6
2046	13	7	254.2	205	64617.64	42025	52111
2047	13	5	75.6	62	5715.36	3844	4687.2
2048	13	10	189.8	152	36024.04	23104	28849.6
3046	13	4	123.4	96	15227.56	9216	11846.4
3047	13	8	221.3	183	48973.69	33489	40497.9
3048	13	6	206.1	170	42477.21	28900	35037
3049	13	8	288.3	223	83116.89	49729	64290.9
3050	13	7	201.1	151	40441.21	22801	30366.1
4043	13	10	164.2	139	26961.64	19321	22823.8
4044	13	1	42.6	37	1814.76	1369	1576.2
4045	13	10	188.2	126	35419.24	15876	23713.2
4046	13	7	104.7	53	10962.09	2809	5549.1
5129	13	5	229.1	190	52486.81	36100	43529
5130	13	6	236.2	176	55790.44	30976	41571.2
5131	13	1	175.5	155	30800.25	24025	27202.5
5132	13	3	211.5	164	44732.25	26896	34686
5133	13	0	112.8	92	12723.84	8464	10377.6
5134	13	2	269.8	191	72792.04	36481	51531.8
6181	13	7	212.8	137	45283.84	18769	29153.6
6182	13	1	134.2	104	18009.64	10816	13956.8
8468	13	2	62.5	52	3906.25	2704	3250
8469	13	13	227.9	164	51938.41	26896	37375.6
8470	13	6	179.3	117	32148.49	13689	20978.1
8471	13	10	185.6	143	34447.36	20449	26540.8
8473	13	12	174.2	132	30345.64	17424	22994.4
8474	13	14	197.6	144	39045.76	20736	28454.4
8475	13	6	128.8	107	16589.44	11449	13781.6
8476	13	20	254.9	190	64974.01	36100	48431
8477	13	3	100	56	10000	3136	5600
8478	13	7	199	134	39601	17956	26666
8479	13	7	265.9	158	70702.81	24964	42012.2
8480	13	2	104.2	74	10857.64	5476	7710.8
8482	13	9	178.9	110	32005.21	12100	19679
8483	13	5	102.2	53	10444.84	2809	5416.6
8484	13	3	66.7	51	4448.89	2601	3401.7
8485	13	6	118.1	66	13947.61	4356	7794.6
8486	13	5	214.1	148	45838.81	21904	31686.8

8487	13	13	218	156	47524	24336	34008
8488	13	11	219.1	173	48004.81	29929	37904.3
8489	13	8	167.7	118	28123.29	13924	19788.6
8490	13	7	304.6	191	92781.16	36481	58178.6
8491	13	12	181	134	32761	17956	24254
8492	13	1	51.9	37	2693.61	1369	1920.3
8493	13	11	244.9	177	59976.01	31329	43347.3
8494	13	9	182.5	138	33306.25	19044	25185
8496	13	9	261.8	157	68539.24	24649	41102.6
8497	13	8	214.9	136	46182.01	18496	29226.4
8498	13	11	234.7	168	55084.09	28224	39429.6
8499	13	11	215.6	141	46483.36	19881	30399.6
8500	13	3	77.1	59	5944.41	3481	4548.9
8501	13	9	254.2	142	64617.64	20164	36096.4
8502	13	6	176.9	127	31293.61	16129	22466.3
8503	13	6	214.4	135	45967.36	18225	28944
8504	13	5	269.6	171	72684.16	29241	46101.6
8505	13	7	216.5	164	46872.25	26896	35506
8506	13	11	113.3	83	12836.89	6889	9403.9
8507	13	5	270.1	172	72954.01	29584	46457.2
8508	13	9	222.3	132	49417.29	17424	29343.6
8509	13	3	191.6	112	36710.56	12544	21459.2
8510	13	5	74	62	5476	3844	4588
8511	13	7	212	156	44944	24336	33072
8512	13	6	109.3	84	11946.49	7056	9181.2
8513	13	5	239.2	161	57216.64	25921	38511.2
8514	13	8	149.5	115	22350.25	13225	17192.5
8515	13	10	188.1	131	35381.61	17161	24641.1
8516	13	5	94.6	65	8949.16	4225	6149
8517	13	10	122.6	83	15030.76	6889	10175.8
8518	13	5	101.4	68	10281.96	4624	6895.2
8519	13	0	11.7	11	136.89	121	128.7
8520	13	7	240.1	159	57648.01	25281	38175.9
8521	13	3	81.9	60	6707.61	3600	4914
8522	13	8	234.4	148	54943.36	21904	34691.2
8523	13	7	164.9	129	27192.01	16641	21272.1
8525	13	4	159.6	117	25472.16	13689	18673.2
8527	13	6	137.1	94	18796.41	8836	12887.4
8528	13	8	308.8	192	95357.44	36864	59289.6
8529	13	9	173.5	138	30102.25	19044	23943
8530	13	5	55.3	46	3058.09	2116	2543.8
8531	13	10	220.2	139	48488.04	19321	30607.8
8532	13	3	173.6	103	30136.96	10609	17880.8
8533	13	9	301.6	192	90962.56	36864	57907.2

8535	13	8	162.8	127	26503.84	16129	20675.6
8536	13	17	233.9	146	54709.21	21316	34149.4
8537	13	6	108.5	75	11772.25	5625	8137.5
8538	13	2	38.5	32	1482.25	1024	1232
8539	13	11	182.6	131	33342.76	17161	23920.6
8541	13	5	166.7	110	27788.89	12100	18337
8542	13	5	58.9	46	3469.21	2116	2709.4
8543	13	19	216.6	123	46915.56	15129	26641.8
8544	13	8	261.8	157	68539.24	24649	41102.6
8545	13	8	220.3	153	48532.09	23409	33705.9
8546	13	10	348.8	230	121661.4	52900	80224
8547	13	17	253.8	168	64414.44	28224	42638.4
8548	13	6	133.3	80	17768.89	6400	10664
8549	13	0	226.4	149	51256.96	22201	33733.6
8561	13	2	113.9	89	12973.21	7921	10137.1
8562	13	4	88.8	66	7885.44	4356	5860.8
8563	13	3	127.9	93	16358.41	8649	11894.7
8564	13	7	257.3	175	66203.29	30625	45027.5
8565	13	12	180.1	135	32436.01	18225	24313.5
8566	13	8	192.7	148	37133.29	21904	28519.6
8567	13	9	245.8	168	60417.64	28224	41294.4
8568	13	19	225.1	179	50670.01	32041	40292.9
8569	13	5	195.4	115	38181.16	13225	22471
8570	13	16	274.4	202	75295.36	40804	55428.8
8571	13	3	39.6	37	1568.16	1369	1465.2
8572	13	17	182.2	151	33196.84	22801	27512.2
8573	13	14	225	174	50625	30276	39150
8574	13	7	129.3	108	16718.49	11664	13964.4
9007	13	3	170.8	120	29172.64	14400	20496
9008	13	5	94.9	67	9006.01	4489	6358.3
9009	13	1	205	138	42025	19044	28290
9011	13	10	191.7	172	36748.89	29584	32972.4
9012	13	9	146	130	21316	16900	18980
9013	13	1	57.4	35	3294.76	1225	2009
9014	13	14	162.4	126	26373.76	15876	20462.4
9016	13	10	197.1	158	38848.41	24964	31141.8
9020	13	5	232.1	153	53870.41	23409	35511.3
9021	13	3	185.2	121	34299.04	14641	22409.2
9022	13	2	418.8	153	175393.4	23409	64076.4
9025	13	2	155.9	67	24304.81	4489	10445.3
9026	13	18	258.7	200	66925.69	40000	51740
9029	13	12	232.6	189	54102.76	35721	43961.4
9030	13	12	189.5	151	35910.25	22801	28614.5
9034	13	8	205.2	161	42107.04	25921	33037.2

9035	13	2	114.3	107	13064.49	11449	12230.1
9036	13	1	370.6	128	137344.4	16384	47436.8
9037	13	0	47.8	40	2284.84	1600	1912
9041	13	5	136	92	18496	8464	12512
9042	13	2	254.9	154	64974.01	23716	39254.6
9046	13	0	112.1	83	12566.41	6889	9304.3
9048	13	5	176	112	30976	12544	19712
9049	13	3	150.9	95	22770.81	9025	14335.5
9050	13	1	258.3	155	66718.89	24025	40036.5
9053	13	2	277	180	76729	32400	49860
9054	13	6	241.5	157	58322.25	24649	37915.5
9056	13	3	207	141	42849	19881	29187
9057	13	5	178	139	31684	19321	24742
9058	13	6	414.6	163	171893.2	26569	67579.8
9059	13	6	185.8	131	34521.64	17161	24339.8
9064	13	12	220.5	191	48620.25	36481	42115.5
9065	13	5	280	181	78400	32761	50680
9066	13	2	240.4	160	57792.16	25600	38464
9068	13	9	148.4	126	22022.56	15876	18698.4
9069	13	9	349.7	156	122290.1	24336	54553.2
9070	13	6	186.8	117	34894.24	13689	21855.6
9072	13	2	414.7	165	171976.1	27225	68425.5
9073	13	1	451.6	150	203942.6	22500	67740
9074	13	9	292.8	192	85731.84	36864	56217.6
9075	13	11	319.4	213	102016.4	45369	68032.2
9076	13	0	350.9	121	123130.8	14641	42458.9
9077	13	7	146.6	112	21491.56	12544	16419.2
9078	13	4	88.6	62	7849.96	3844	5493.2
9079	13	8	294.6	200	86789.16	40000	58920
9080	13	8	248.3	173	61652.89	29929	42955.9
	TOTAL	1560	48337.5	32057			

Table C-2. 1994 FORTRAN Program Data Output Sample

TAIL	WUC	DMDS	CUMFH	NSORT	CUMFH2	NSORT2	FHNSORT
2	11	0	178.2	133	31755.24	17689	23700.6
3	11	1	142.5	115	20306.25	13225	16387.5
4	11	0	205	95	42025	9025	19475
5	11	1	180.6	149	32616.36	22201	26909.4
6	11	7	131.1	133	17187.21	17689	17436.3
9	11	3	175.7	120	30870.49	14400	21084
10	11	3	186.9	161	34931.61	25921	30090.9
11	11	2	185.7	130	34484.49	16900	24141
12	11	4	318.8	106	101633.4	11236	33792.8
13	11	2	166.8	118	27822.24	13924	19682.4
14	11	1	147.5	113	21756.25	12769	16667.5
15	11	10	169.5	141	28730.25	19881	23899.5
16	11	11	168.2	134	28291.24	17956	22538.8
18	11	0	130.9	92	17134.81	8464	12042.8
19	11	6	142.6	121	20334.76	14641	17254.6
20	11	8	260.9	139	68068.81	19321	36265.1
21	11	0	131.3	83	17239.69	6889	10897.9
22	11	0	148.2	105	21963.24	11025	15561
24	11	0	150.1	90	22530.01	8100	13509
26	11	7	170.4	134	29036.16	17956	22833.6
27	11	5	112.2	79	12588.84	6241	8863.8
28	11	2	164.4	156	27027.36	24336	25646.4
29	11	0	168.8	106	28493.44	11236	17892.8
30	11	3	90	82	8100	6724	7380
31	11	3	172.4	157	29721.76	24649	27066.8
33	11	13	186.1	180	34633.21	32400	33498
34	11	7	127.3	136	16205.29	18496	17312.8
35	11	1	115	75	13225	5625	8625
38	11	0	77	52	5929	2704	4004
39	11	2	159.1	108	25312.81	11664	17182.8
40	11	0	157.9	121	24932.41	14641	19105.9
42	11	0	168.4	114	28358.56	12996	19197.6
43	11	6	141	129	19881	16641	18189
44	11	8	160	154	25600	23716	24640
45	11	4	131.4	128	17265.96	16384	16819.2
46	11	0	9.8	2	96.04	4	19.6
47	11	0	52.7	28	2777.29	784	1475.6
48	11	1	158.4	84	25090.56	7056	13305.6
49	11	3	132.1	124	17450.41	15376	16380.4
50	11	2	129.2	79	16692.64	6241	10206.8
51	11	1	184.3	107	33966.49	11449	19720.1

52	11	0	160.9	105	25888.81	11025	16894.5
53	11	4	197.2	124	38887.84	15376	24452.8
1020	11	0	172.6	108	29790.76	11664	18640.8
1021	11	1	182.7	110	33379.29	12100	20097
1022	11	5	136.4	96	18604.96	9216	13094.4
1023	11	0	196.8	85	38730.24	7225	16728
1024	11	3	174.7	143	30520.09	20449	24982.1
1025	11	4	205.3	146	42148.09	21316	29973.8
1026	11	4	165	113	27225	12769	18645
1027	11	0	39.9	31	1592.01	961	1236.9
1028	11	1	169.8	122	28832.04	14884	20715.6
1029	11	10	271	209	73441	43681	56639
1030	11	1	187.8	134	35268.84	17956	25165.2
1031	11	5	153.8	114	23654.44	12996	17533.2
1032	11	3	225.9	133	51030.81	17689	30044.7
1033	11	2	146	76	21316	5776	11096
1034	11	0	202	147	40804	21609	29694
1035	11	0	215.9	142	46612.81	20164	30657.8
1036	11	0	187.5	119	35156.25	14161	22312.5
1037	11	2	219.1	127	48004.81	16129	27825.7
1038	11	1	68.2	39	4651.24	1521	2659.8
1039	11	1	165.7	122	27456.49	14884	20215.4
1040	11	3	222.3	156	49417.29	24336	34678.8
1041	11	2	201.9	140	40763.61	19600	28266
1042	11	3	214.6	144	46053.16	20736	30902.4
1043	11	4	239.9	148	57552.01	21904	35505.2
1044	11	0	164.6	116	27093.16	13456	19093.6
1045	11	0	159.2	115	25344.64	13225	18308
1046	11	11	191.2	144	36557.44	20736	27532.8
1047	11	3	220.9	133	48796.81	17689	29379.7
1048	11	0	148.4	126	22022.56	15876	18698.4
1050	11	2	191.8	145	36787.24	21025	27811
1051	11	2	191.5	127	36672.25	16129	24320.5
1053	11	6	162.2	167	26308.84	27889	27087.4
1054	11	0	210.5	143	44310.25	20449	30101.5
1055	11	8	119.5	120	14280.25	14400	14340
2008	11	5	199.4	165	39760.36	27225	32901
2009	11	0	144	54	20736	2916	7776
2010	11	6	184.5	144	34040.25	20736	26568
2011	11	0	54	40	2916	1600	2160
2012	11	1	155.6	125	24211.36	15625	19450
2013	11	1	140.2	101	19656.04	10201	14160.2
2014	11	0	14	14	196	196	196
2015	11	0	158.5	114	25122.25	12996	18069

2016	11	3	145.2	116	21083.04	13456	16843.2
2017	11	2	243.5	116	59292.25	13456	28246
2018	11	1	263.6	153	69484.96	23409	40330.8
2019	11	0	183.4	125	33635.56	15625	22925
2021	11	2	209.8	145	44016.04	21025	30421
2022	11	1	132.9	96	17662.41	9216	12758.4
2023	11	1	151.2	118	22861.44	13924	17841.6
2024	11	1	173.3	127	30032.89	16129	22009.1
2025	11	1	263.1	138	69221.61	19044	36307.8
2026	11	0	44.7	37	1998.09	1369	1653.9
2027	11	0	80.6	62	6496.36	3844	4997.2
2028	11	4	160.8	101	25856.64	10201	16240.8
2029	11	1	261.4	138	68329.96	19044	36073.2
2030	11	1	153.7	125	23623.69	15625	19212.5
2031	11	0	104.8	83	10983.04	6889	8698.4
2032	11	6	145.1	100	21054.01	10000	14510
2033	11	0	170	155	28900	24025	26350
2034	11	8	144.6	113	20909.16	12769	16339.8
2035	11	4	154.9	123	23994.01	15129	19052.7
2036	11	1	168.2	122	28291.24	14884	20520.4
2037	11	3	173.4	103	30067.56	10609	17860.2
2038	11	1	276.9	142	76673.61	20164	39319.8
3010	11	6	228.1	164	52029.61	26896	37408.4
3011	11	1	184.9	127	34188.01	16129	23482.3
3012	11	8	260.5	150	67860.25	22500	39075
3013	11	0	236.6	111	55979.56	12321	26262.6
3014	11	1	226.5	135	51302.25	18225	30577.5
3015	11	0	190.7	128	36366.49	16384	24409.6
3016	11	7	196.2	143	38494.44	20449	28056.6
3017	11	1	71.4	86	5097.96	7396	6140.4
3018	11	3	115.2	90	13271.04	8100	10368
3019	11	3	153.5	114	23562.25	12996	17499
3020	11	4	174.9	137	30590.01	18769	23961.3
3022	11	4	150.9	116	22770.81	13456	17504.4
3023	11	2	104.5	91	10920.25	8281	9509.5
3024	11	2	249.5	133	62250.25	17689	33183.5
3025	11	2	242.9	151	59000.41	22801	36677.9
3026	11	2	258.3	166	66718.89	27556	42877.8
3027	11	3	194.5	141	37830.25	19881	27424.5
3028	11	1	84.4	65	7123.36	4225	5486
3029	11	1	37.8	17	1428.84	289	642.6
3030	11	1	17.7	18	313.29	324	318.6
3031	11	6	111.7	84	12476.89	7056	9382.8
3032	11	1	189.4	146	35872.36	21316	27652.4

3033	11	2	186.2	151	34670.44	22801	28116.2
3034	11	4	188.7	142	35607.69	20164	26795.4
3035	11	0	124.8	106	15575.04	11236	13228.8
3036	11	4	225.8	166	50985.64	27556	37482.8
3037	11	2	169.5	115	28730.25	13225	19492.5
3038	11	1	195.5	152	38220.25	23104	29716
3039	11	4	271.1	153	73495.21	23409	41478.3
3040	11	0	155.9	138	24304.81	19044	21514.2
3041	11	0	185.2	114	34299.04	12996	21112.8
3042	11	4	229.9	171	52854.01	29241	39312.9
3043	11	3	131	104	17161	10816	13624
4001	11	2	180.1	114	32436.01	12996	20531.4
4002	11	8	161.6	119	26114.56	14161	19230.4
4003	11	0	76.7	28	5882.89	784	2147.6
4004	11	2	155	117	24025	13689	18135
4005	11	4	201.8	131	40723.24	17161	26435.8
4006	11	11	279.4	148	78064.36	21904	41351.2
4007	11	13	153.4	115	23531.56	13225	17641
4008	11	1	274.8	148	75515.04	21904	40670.4
4009	11	6	270.2	120	73008.04	14400	32424
4010	11	3	157.3	124	24743.29	15376	19505.2
4011	11	10	238.1	182	56691.61	33124	43334.2
4012	11	2	136.3	114	18577.69	12996	15538.2
4013	11	2	143	97	20449	9409	13871
4014	11	2	198.4	85	39362.56	7225	16864
4015	11	4	316	126	99856	15876	39816
4016	11	5	180.1	143	32436.01	20449	25754.3
4017	11	0	156.8	100	24586.24	10000	15680
4018	11	12	199.3	154	39720.49	23716	30692.2
4019	11	9	158.3	126	25058.89	15876	19945.8
4020	11	2	142.1	116	20192.41	13456	16483.6
5094	11	1	219.5	154	48180.25	23716	33803
5095	11	3	55.6	44	3091.36	1936	2446.4
5096	11	0	328.5	91	107912.3	8281	29893.5
5097	11	0	514	129	264196	16641	66306
5098	11	2	151.6	128	22982.56	16384	19404.8
5099	11	4	200.3	137	40120.09	18769	27441.1
5100	11	0	489.9	129	240002	16641	63197.1
5101	11	0	117	97	13689	9409	11349
5102	11	2	154.5	124	23870.25	15376	19158
5103	11	2	201.3	128	40521.69	16384	25766.4
5104	11	8	118.8	119	14113.44	14161	14137.2
5105	11	0	627.2	155	393379.8	24025	97216
5106	11	1	539.7	130	291276.1	16900	70161

5107	11	0	521	132	271441	17424	68772
5108	11	2	324.8	113	105495	12769	36702.4
5110	11	2	205.1	140	42066.01	19600	28714
5111	11	1	177.2	134	31399.84	17956	23744.8
5112	11	0	288.3	146	83116.89	21316	42091.8
5113	11	6	276.7	203	76562.89	41209	56170.1
5114	11	4	127.3	94	16205.29	8836	11966.2
5115	11	3	140.9	118	19852.81	13924	16626.2
5117	11	0	324	108	104976	11664	34992
5118	11	0	504.6	122	254621.2	14884	61561.2
5119	11	2	236.5	101	55932.25	10201	23886.5
5120	11	5	148	120	21904	14400	17760
5121	11	1	280.7	183	78792.49	33489	51368.1
5122	11	2	157.6	112	24837.76	12544	17651.2
5123	11	6	223.3	153	49862.89	23409	34164.9
5124	11	3	373.2	115	139278.2	13225	42918
5125	11	0	384.2	143	147609.6	20449	54940.6
5126	11	3	176.9	135	31293.61	18225	23881.5
5127	11	2	131.4	108	17265.96	11664	14191.2
5128	11	2	140.5	129	19740.25	16641	18124.5
6143	11	0	126.2	100	15926.44	10000	12620
6144	11	1	135.8	98	18441.64	9604	13308.4
6145	11	4	179.8	104	32328.04	10816	18699.2
6146	11	0	174	123	30276	15129	21402
6147	11	4	147.5	122	21756.25	14884	17995
6148	11	3	145.6	104	21199.36	10816	15142.4
6149	11	3	206.3	126	42559.69	15876	25993.8
6150	11	4	263.6	173	69484.96	29929	45602.8
6151	11	4	219.2	139	48048.64	19321	30468.8
6152	11	1	199.6	131	39840.16	17161	26147.6
6154	11	0	92.1	64	8482.41	4096	5894.4
6155	11	2	246.5	145	60762.25	21025	35742.5
6156	11	1	150.7	92	22710.49	8464	13864.4
6157	11	0	54.9	46	3014.01	2116	2525.4
6158	11	4	208	126	43264	15876	26208
6159	11	2	101.4	47	10281.96	2209	4765.8
6160	11	0	28.6	24	817.96	576	686.4
6161	11	0	64.2	39	4121.64	1521	2503.8
6162	11	4	190.5	126	36290.25	15876	24003
6163	11	4	158.5	121	25122.25	14641	19178.5
6164	11	2	92.2	70	8500.84	4900	6454
6165	11	0	113.6	89	12904.96	7921	10110.4
6166	11	1	102.7	80	10547.29	6400	8216
6167	11	0	188	75	35344	5625	14100

6168	11	7	111.2	100	12365.44	10000	11120
6169	11	0	153.3	109	23500.89	11881	16709.7
6170	11	2	126.7	84	16052.89	7056	10642.8
6171	11	4	125.8	70	15825.64	4900	8806
6172	11	0	88.5	73	7832.25	5329	6460.5
6173	11	1	104.4	63	10899.36	3969	6577.2
6174	11	0	150.9	104	22770.81	10816	15693.6
6175	11	0	200.5	26	40200.25	676	5213
6176	11	2	133	70	17689	4900	9310
6177	11	1	139	103	19321	10609	14317
6178	11	1	102	97	10404	9409	9894
6179	11	0	167.4	156	28022.76	24336	26114.4
6180	11	2	108.4	99	11750.56	9801	10731.6
8468	11	1	179.2	129	32112.64	16641	23116.8
8469	11	0	97.9	88	9584.41	7744	8615.2
8470	11	7	131.1	115	17187.21	13225	15076.5
8471	11	4	170.5	125	29070.25	15625	21312.5
8473	11	0	175.4	130	30765.16	16900	22802
8474	11	0	168.9	128	28527.21	16384	21619.2
8475	11	0	108.1	94	11685.61	8836	10161.4
8476	11	0	199.8	153	39920.04	23409	30569.4
8478	11	0	124	87	15376	7569	10788
8479	11	0	31.7	24	1004.89	576	760.8
8480	11	3	182.1	139	33160.41	19321	25311.9
8483	11	0	178.3	110	31790.89	12100	19613
8485	11	0	72	47	5184	2209	3384
8486	11	1	138.5	106	19182.25	11236	14681
8487	11	7	170	139	28900	19321	23630
8488	11	0	152.1	119	23134.41	14161	18099.9
8489	11	2	188.9	138	35683.21	19044	26068.2
8490	11	5	227.2	141	51619.84	19881	32035.2
8491	11	1	73.6	52	5416.96	2704	3827.2
8492	11	1	212.9	154	45326.41	23716	32786.6
8493	11	1	129.9	90	16874.01	8100	11691
8494	11	0	86.8	67	7534.24	4489	5815.6
8496	11	0	182.6	139	33342.76	19321	25381.4
8497	11	0	89.8	71	8064.04	5041	6375.8
8498	11	0	109.6	84	12012.16	7056	9206.4
8499	11	2	141.1	113	19909.21	12769	15944.3
8500	11	0	142.7	105	20363.29	11025	14983.5
8502	11	0	109.4	75	11968.36	5625	8205
8503	11	5	148.9	109	22171.21	11881	16230.1
8504	11	1	122.4	101	14981.76	10201	12362.4
8505	11	9	152.7	122	23317.29	14884	18629.4

8506	11	1	251.8	105	63403.24	11025	26439
8507	11	6	220.3	141	48532.09	19881	31062.3
8508	11	4	161.1	124	25953.21	15376	19976.4
8509	11	1	138.9	119	19293.21	14161	16529.1
8510	11	0	147.5	114	21756.25	12996	16815
8511	11	0	119.9	97	14376.01	9409	11630.3
8512	11	2	163.3	131	26666.89	17161	21392.3
8513	11	0	195.3	122	38142.09	14884	23826.6
8514	11	3	144.1	129	20764.81	16641	18588.9
8515	11	0	155.4	108	24149.16	11664	16783.2
8516	11	3	199.4	146	39760.36	21316	29112.4
8517	11	4	202.1	131	40844.41	17161	26475.1
8518	11	1	247.7	154	61355.29	23716	38145.8
8519	11	1	178.1	132	31719.61	17424	23509.2
8520	11	0	116.4	79	13548.96	6241	9195.6
8521	11	0	204.5	137	41820.25	18769	28016.5
8522	11	0	133	104	17689	10816	13832
8523	11	0	171.3	127	29343.69	16129	21755.1
8525	11	0	167.2	127	27955.84	16129	21234.4
8527	11	0	56.6	41	3203.56	1681	2320.6
8528	11	1	230.2	152	52992.04	23104	34990.4
8529	11	1	186.5	144	34782.25	20736	26856
8530	11	2	128.1	88	16409.61	7744	11272.8
8531	11	0	212.4	134	45113.76	17956	28461.6
8532	11	0	68	43	4624	1849	2924
8533	11	2	189	125	35721	15625	23625
8535	11	4	122.2	85	14932.84	7225	10387
8536	11	0	201.7	127	40682.89	16129	25615.9
8537	11	0	74.5	52	5550.25	2704	3874
8538	11	2	164.3	125	26994.49	15625	20537.5
8539	11	0	164.9	124	27192.01	15376	20447.6
8541	11	0	179	113	32041	12769	20227
8542	11	2	140.6	126	19768.36	15876	17715.6
8543	11	1	90.3	70	8154.09	4900	6321
8544	11	3	145.4	105	21141.16	11025	15267
8545	11	1	194.4	118	37791.36	13924	22939.2
8546	11	5	249.5	137	62250.25	18769	34181.5
8547	11	0	32.6	43	1062.76	1849	1401.8
8548	11	0	63.6	48	4044.96	2304	3052.8
8549	11	9	847	151	717409	22801	127897
8550	11	1	98.2	50	9643.24	2500	4910
9016	11	4	101.8	82	10363.24	6724	8347.6
9020	11	0	187.6	128	35193.76	16384	24012.8
9021	11	3	90.2	55	8136.04	3025	4961

9022	11	3	210.8	119	44436.64	14161	25085.2
9025	11	4	346.2	123	119854.4	15129	42582.6
9026	11	2	154.9	136	23994.01	18496	21066.4
9029	11	6	139	121	19321	14641	16819
9030	11	2	116.4	110	13548.96	12100	12804
9034	11	5	173.5	120	30102.25	14400	20820
9035	11	2	201.5	167	40602.25	27889	33650.5
9036	11	1	116.1	89	13479.21	7921	10332.9
9037	11	2	165.3	126	27324.09	15876	20827.8
9041	11	1	82.9	48	6872.41	2304	3979.2
9042	11	0	143.7	96	20649.69	9216	13795.2
9046	11	2	173.7	147	30171.69	21609	25533.9
9049	11	1	1229.9	173	1512654	29929	212772.7
9050	11	2	267	172	71289	29584	45924
9053	11	3	24.6	10	605.16	100	246
9054	11	0	50.9	33	2590.81	1089	1679.7
9056	11	2	152.7	102	23317.29	10404	15575.4
9057	11	2	191.8	112	36787.24	12544	21481.6
9058	11	2	126.5	91	16002.25	8281	11511.5
9059	11	4	194.5	131	37830.25	17161	25479.5
9064	11	6	286.3	158	81967.69	24964	45235.4
9065	11	3	258.2	160	66667.24	25600	41312
9066	11	1	216.6	130	46915.56	16900	28158
9068	11	0	173.7	134	30171.69	17956	23275.8
9069	11	5	195.4	163	38181.16	26569	31850.2
9070	11	0	6.4	4	40.96	16	25.6
9072	11	5	179.5	133	32220.25	17689	23873.5
9073	11	2	139	93	19321	8649	12927
9074	11	1	227.9	152	51938.41	23104	34640.8
9075	11	7	185.4	132	34373.16	17424	24472.8
9076	11	5	166.7	124	27788.89	15376	20670.8
9077	11	0	135.2	112	18279.04	12544	15142.4
9078	11	2	174.3	97	30380.49	9409	16907.1
9079	11	0	132.1	85	17450.41	7225	11228.5
9080	11	10	272.4	175	74201.76	30625	47670
	TOTALS	794	60254.5	38666			

Appendix D: Multiple Regression Results, Hypothesis Testing, and Residual Calculations

Table D-1. Multiple Regression Results at the Two-Digit Work Unit Code Level

Two-Digit Work Unit Code Level	R-Squared	Durbin-Watson Statistic
11	0.0525	1.9574
12	0.0929	1.9420
13	0.2901	1.6189
14	0.0615	2.0383
23	0.2134	2.1051
24	0.0756	1.7635
41	0.0614	2.0368
42	0.0561	2.0909
44	0.1310	1.9953
45	0.0698	1.7640
46	0.1594	1.9672
47	0.0914	1.9924
49	0.0205	2.0391
51	0.1789	1.6510
52	0.0229	2.0665
55	0.0295	2.1670
57	0.0388	1.6796
63	0.1999	1.9403
65	0.1074	1.7577
71	0.1163	1.9307
74	0.3492	2.1225
75	0.0759	1.9376
76	0.2522	1.9698
97	0.0182	1.4665

Table D-2. Multiple Regression Results at the Three-Digit Work Unit Code Level

Three-Digit Work Unit Code Level	R-Squared	Durbin-Watson Statistic
11A	0.0230	2.1474
11G	0.0061	1.7838
11K	0.0206	1.9703
11P	0.0234	1.9081
12C	0.0220	2.2048
12E	0.0728	2.1067
13A	0.2412	1.6609
13B	0.0724	2.0657
13D	0.0260	2.1315
13F	0.0084	1.8672
13H	0.0058	1.9034
14A	0.0426	2.0302
14C	0.0131	2.0907
14D	0.0336	1.9797
14G	0.0067	2.0680
231	0.0946	1.8876
23F	0.0586	2.2327
23H	0.0446	2.2055
23K	0.0373	2.1012
23P	0.0309	1.8887
23Q	0.0168	2.0020
23Z	0.0430	2.0665
24A	0.0249	1.7457
24B	0.0433	1.8595
24D	0.0247	1.9201
41A	0.0608	2.2055
42A	0.0501	2.0501
42C	0.0002	2.0325
44A	0.1307	1.9989
44B	0.0245	2.1242
44E	0.0048	2.0092
45A	0.0390	1.8893
45B	0.0078	1.8874
45C	0.0447	1.8974
46A	0.0694	2.0272
46B	0.2429	2.1105
46E	0.0768	2.0991
47A	0.0914	1.9924
49A	0.0084	2.0310
51A	0.1307	1.9001

51E	0.0396	1.9314
51M	0.0583	1.8195
51N	0.0492	1.5113
52A	0.0229	2.0665
55A	0.0131	2.0782
55B	0.0133	2.2440
55C	0.0125	1.9785
57A	0.0364	1.6815
63A	0.1480	1.9293
63B	0.0961	2.0761
63E	0.0156	2.1430
65A	0.0572	2.0053
65B	0.0717	1.7196
71A	0.0126	2.0112
71C	0.0244	1.9800
71F	0.0619	1.8191
71M	0.0367	1.9671
71Z	0.0277	1.8990
74E	0.0202	2.0803
74F	0.2720	1.9823
74J	0.0578	2.1457
74K	0.0595	2.1790
74L	0.0521	2.0844
75B	0.0728	1.6988
75E	0.0180	1.8724
75G	0.0019	1.5684
75M	0.0054	2.1472
75P	0.0210	2.0404
76A	0.1039	1.8724
76B	0.0454	1.9337
76G	0.1384	2.0169
76H	0.2050	1.8456
76K	0.0324	1.9537
97A	0.0182	1.4665

Table D-3. Multiple Regression Results at the Five-Digit Work Unit Code Level

Five-Digit Work Unit Code Level	R-Squared	Durbin-Watson Statistic
11A99	0.0045	2.0258
11AB0	0.0381	2.0695
13AK0	0.0664	1.3208
13AKA	0.1344	1.6445
13AKB	0.0412	1.1493
13BJ0	0.0253	1.7670
13BJA	0.0188	2.0721
13BJB	0.0610	1.6475
13DC0	0.0028	1.8629
14AAA	0.0119	1.7964
14DDA	0.0114	1.8753
231AA	0.0073	2.0465
231AB	0.0158	2.0510
231AM	0.0389	1.9780
231FN	0.0153	1.7092
23FBA	0.0222	2.1064
23HAA	0.0157	1.9451
23HAB	0.0387	1.9737
23PAB	0.0312	1.8756
23QAN	0.0878	2.0846
23Z00	0.0430	2.0665
24AD0	0.0188	1.8656
24AN0	0.0251	1.8597
24BA0	0.0118	2.1282
24BAC	0.0070	1.8751
24DAD	0.0193	2.0084
41AEH	0.0141	1.9702
42AD0	0.0248	1.9303
42ADA	0.0220	1.8653
42ADB	0.0252	1.9858
42AF0	0.0219	1.6833
44A99	0.0249	2.0473
44AAA	0.0338	1.9766
44AAC	0.0401	1.8672
44AAL	0.0170	1.7640
44AAY	0.0246	1.9899
46EBB	0.0109	1.9957
47AAH	0.0456	2.0320
47AAX	0.0306	2.0348

51AD0	0.0059	2.0632
51AE0	0.0148	2.1236
51AF0	0.1185	1.8077
51AJ0	0.0342	1.9295
51AK0	0.0371	2.1234
51EA0	0.0123	1.8769
51ED0	0.0189	1.8679
51EF0	0.0395	2.0289
51MA0	0.0655	1.7841
51NA0	0.0385	1.6626
51NB0	0.0173	2.0315
52AA0	0.0244	2.0084
52AB0	0.0132	2.0423
52AC0	0.0066	1.9469
55AE0	0.0095	2.0332
55BC0	0.0111	2.1136
55BE0	0.0101	2.2148
55CB0	0.0117	1.9678
57AC0	0.0236	1.4634
63AD0	0.0651	1.9364
63AN0	0.0138	2.0816
63AT0	0.0127	2.1176
63AV0	0.0765	1.8931
63BH0	0.0266	1.9878
63BJ0	0.0749	1.8576
65AA0	0.0493	1.9606
65AB0	0.0379	2.0633
65BA0	0.0239	2.0292
65BB0	0.0449	1.9590
65BC0	0.0203	1.8960
65BH0	0.0391	1.5730
71AK0	0.0105	2.0557
71CA0	0.0265	1.9402
71FA0	0.0626	1.9594
71FB0	0.0465	1.7997
71FE0	0.0043	2.0911
71MA0	0.0375	2.0677
71ZA0	0.0447	2.0573
71ZF0	0.0026	1.7985
74EB0	0.0202	2.0803
74FA0	0.1127	2.0015
74FC0	0.0762	2.0209

74FH0	0.0578	1.9339
74FJ0	0.0973	2.0292
74FQ0	0.0468	2.1193
74FS0	0.1247	1.8172
74FU0	0.0728	1.9853
74FY0	0.0452	2.0396
74JA0	0.0451	2.0370
74JE0	0.0009	2.2456
74KA0	0.0647	2.1417
74KC0	0.0226	2.1947
74LB0	0.0558	1.9746
75BB0	0.0263	1.8835
75BD0	0.0369	1.7991
75BH0	0.0178	1.7788
75EB0	0.0180	1.8724
75GA0	0.0018	1.5485
75MA0	0.0033	2.1269
75MC0	0.0057	2.1082
75PA0	0.0210	2.0404
76AA0	0.0374	1.8559
76AC0	0.0733	1.9720
76AD0	0.0412	2.0224
76AG0	0.0153	1.9021
76BA0	0.0364	1.9692
76BB0	0.0307	1.9290
76BD0	0.0087	2.0252
76GF0	0.1131	2.0127
76HA0	0.0251	1.8808
76HB0	0.2288	1.9382
76HF0	0.0101	1.8524
76HG0	0.1929	2.1541
76KA0	0.0051	2.0164
76KC0	0.0254	1.7922
97ABD	0.0160	1.8016

Reduced and Full Model Multiple Regressions and Hypothesis Testing for Two Digit Work Unit Code 13:

Unweighted Least Squares Linear Regression of Demands (Reduced Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	0.80062	0.2375
CUMFH	-0.02052	0.0000
NSORT	0.07344	0.0000

R- Squared: 0.2901; Adjusted R-Squared: 0.2843; Sum of Squares Error (SSE1): 2875.87

Hypothesis Testing: Ho: $\beta_1 = \beta_2 = ... = \beta_k = 0$

Ha: at least one $\beta_i \neq 0$ (i = 1,.......,k)

$R^2 = 0.2901$
n = number of data points = 247
k = number of carriers = 2

Test Statistic Value: $f = \frac{R^2/k}{(1-R^2)/[n-(k+1)]} = \frac{0.2901/2}{(1-0.2901)/[247-(2+1)]} = 49.86$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,244} = 3.00$ (Table A-4, Neter and Wasserman, 1974:812)

Since 49.86>>3.00, the null hypothesis is rejected and the conclusion is demands/ maintenance actions is linearly related to at least one of the predictor variables.

Now, the test to determine if additional carriers can improve the reduced model:

Unweighted Least Squares Linear Regression of Demands (Full Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	0.47398	0.6997
CUMFH	-3.915E-04	0.9832
NSORT	0.04954	0.1658
CUMFH2	-3.519E-05	0.4683
NSORT2	3.838E-05	0.8839
CUMFHNSORT	1.398E-05	0.9496

R-Squared: 0.2954; Adjusted R-Squared: 0.2808
Sum of Squares Error (SSE2): 2854.50; Residual Mean Square (MSE2): 11.8444

Hypothesis Testing:

Ho: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$ (reduced model)
Ha: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$ (full model)
The number of points, n, = 247
The number of regressors in full model, k, = 5; therefore (n-(k+1)) = 247 - 6 = 241

The number of additional regressor variables, p, = 3

Test Statistic Value: $f = \dfrac{(SSE1 - SSE2)/p}{MSE2} = \dfrac{(2875.87 - 2854.50)/3}{11.8444} = 0.6014$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,241} = 2.60$ (Table A-4, Neter and Wasserman, 1974:812)

Since 0.6014 < 2.60, the decision is to accept the null hypothesis and conclude additional variables do not contribute to the model. Therefore, the reduced model will be used to calculate a residual.

Based on p-values for the reduced model, CUMFH and NSORT contribute to the reduced model (The p-values are less than $\alpha = 0.05$). Thus, the reduced model takes the following form: $Y = -0.02052x_1 + 0.07344x_2$. Y represents the expected number of demands or maintenance actions. x_1 represents cumulative flying hours and x_2 represents the number of sorties.

Residual computation: The cumulative flying hour total from the 1994 validation data set is 60,254.5 and the total number of sorties is 38,666. Substituting these values into the reduced model yields $Y = -0.02052(60{,}254.5) + 0.07344(38{,}666) = 1{,}321.22$ or approximately 1,321 expected demands or maintenance actions for 60,254.5 flying hours and 38,666 sorties. The actual number of 13 demands or maintenance actions from the 1994 data is 2,092. Therefore, the residual on the reduced multiple regression model is 2,092 - 1,321 = 771.

Reduced and Full Model Multiple Regressions and Hypothesis Testing for Two Digit Work Unit Code 23:

Unweighted Least Squares Linear Regression of Demands (Reduced Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	-0.04772	0.9320
CUMFH	-0.00683	0.0317
NSORT	0.04257	0.0000

R- Squared: 0.2134; Adjusted R-Squared: 0.2070; Sum of Squares Error (SSE1): 1964.91

Hypothesis Testing: Ho: $\beta_1 = \beta_2 = ... = \beta_k = 0$

Ha: at least one $\beta_i \neq 0$ (i = 1,.......,k)

$R^2 = 0.2134$

n = number of data points = 247

k = number of carriers = 2

Test Statistic Value: $f = \dfrac{R^2 / k}{(1-R^2)/[n-(k+1)]} = \dfrac{0.2134/2}{(1-0.2134)/[247-(2+1)]} = 33.10$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,244} = 3.00$ (Table A-4, Neter and Wasserman, 1974:812)

Since 33.10>>3.00, the null hypothesis is rejected and the conclusion is demands/ maintenance actions is linearly related to at least one of the predictor variables.

Now, the test to determine if additional carriers can improve the reduced model:

Unweighted Least Squares Linear Regression of Demands (Full Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	1.48347	0.1392
CUMFH	0.01328	0.3811
NSORT	-0.01725	0.5530
CUMFH2	-7.609E-05	0.0551
NSORT2	-4.375E-05	0.8382
CUMFHNSORT	1.757E-05	0.3304

R-Squared: 0.2415; Adjusted R-Squared: 0.2258

Sum of Squares Error (SSE2): 1894.71; Residual Mean Square (MSE2): 7.86188

Hypothesis Testing:

Ho: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$ (reduced model)

Ha: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$ (full model)

The number of points, n, = 247

The number of regressors in full model, k, = 5; therefore (n-(k+1)) = 247 - 6 = 241

The number of additional regressor variables, p, = 3

Test Statistic Value: $f = \dfrac{(SSE1 - SSE2)/p}{MSE2} = \dfrac{(1964.91 - 1894.71)/3}{7.86188} = 2.97$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,241} = 2.60$ (Table A-4, Neter and Wasserman, 1974:812)

Since 2.97 > 2.60, the decision is to reject the null hypothesis and conclude additional variables do contribute to the model. Therefore, the full model will be used to calculate a residual.

However, based on p-values for the full model, none of the predictor variables contribute to the full model (None of the p-values are less than $\alpha = 0.05$). Thus, a residual will not be calculated on the full model.

Reduced and Full Model Multiple Regressions and Hypothesis Testing for Two Digit Work Unit Code 63:

Unweighted Least Squares Linear Regression of Demands (Reduced Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	-0.29133	0.5301
CUMFH	-0.00584	0.0266
NSORT	0.03435	0.0000

R- Squared: 0.1999; Adjusted R-Squared: 0.1933; Sum of Squares Error (SSE1): 1350.48

HypothesisTesting: Ho: $\beta_1 = \beta_2 = ... = \beta_k = 0$

Ha: at least one $\beta_i \neq 0$ (i = 1,.......,k)

$R^2 = 0.1999$

n = number of data points = 247

k = number of carriers = 2

Test Statistic Value: $f = \dfrac{R^2 / k}{(1-R^2)/[n-(k+1)]} = \dfrac{0.1999/2}{(1-0.1999)/[247-(2+1)]} = 30.48$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,244} = 3.00$ (Table A-4, Neter and Wasserman, 1974:812)

Since 30.48 >>3.00, the null hypothesis is rejected and the conclusion is demands/ maintenance actions is linearly related to at least one of the predictor variables.

Now, the test to determine if additional carriers can improve the reduced model:

Unweighted Least Squares Linear Regression of Demands (Full Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	0.47760	0.5711
CUMFH	-0.00105	0.9344
NSORT	0.01220	0.6183
CUMFH2	-3.863E-08	0.9991
NSORT2	1.091E-05	0.5454
CUMFHNSORT	-3.096E-05	0.8385

R-Squared: 0.2042; Adjusted R-Squared: 0.1877

Sum of Squares Error (SSE2): 1343.20; Residual Mean Square (MSE2): 5.57344

Hypothesis Testing:

Ho: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$ (reduced model)

Ha: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$ (full model)

The number of points, n, = 247

The number of regressors in full model, k, = 5; therefore (n-(k+1)) = 247 - 6 = 241

The number of additional regressor variables, p, = 3

Test Statistic Value: $f = \frac{(SSE1 - SSE2)/p}{MSE2} = \frac{(1350.48 - 1343.20)/3}{5.57344} = 1.306$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,241} = 2.60$ (Table A-4, Neter and Wasserman, 1974:812)

Since 1.306 < 2.60, the decision is to accept the null hypothesis and conclude additional variables do not contribute to the model. Therefore, the reduced model will be used to calculate a residual.

Based on p-values for the reduced model, the CUMFH and NSORT predictor variables contribute to the reduced model (the p-values are less than $\alpha = 0.05$). The reduced model takes the following form: $Y = -0.00584x_1 + 0.03435x_2$. Y represents the expected number of demands or maintenance actions. x_1 represents cumulative flying hours and x_2 represents the number of sorties.

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Residual computation: The cumulative flying hour total from the 1994 validation data set is 60,254.5 and the total number of sorties is 38,666. Substituting these values into the reduced model yields $Y = -0.00584(60{,}254.5) + 0.03435(38{,}666) = 976.29$ or approximately 976 expected demands or maintenance actions for 60,254.5 flying hours and 38,666 sorties. The actual number of 63 demands or maintenance actions from the 1994 data is 1,057. Therefore, the residual on the reduced multiple regression model is 1,057 - 976 = 81.

Reduced and Full Model Multiple Regressions and Hypothesis Testing for Two Digit Work Unit Code 74:

Unweighted Least Squares Linear Regression of Demands (Reduced Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	-0.32329	0.7532
CUMFH	-0.01133	0.0521
NSORT	0.10203	0.0000

R- Squared: 0.3492; Adjusted R-Squared: 0.3439; Sum of Squares Error (SSE1): 6636.40

Hypothesis Testing: Ho: $\beta_1 = \beta_2 = ... = \beta_k = 0$

Ha: at least one $\beta_i \neq 0$ (i = 1,.......,k)

$R^2 = 0.3492$
n = number of data points = 247
k = number of carriers = 2

Test Statistic Value: $f = \dfrac{R^2 / k}{(1-R^2)/[n-(k+1)]} = \dfrac{0.3492/2}{(1-0.3492)/[247-(2+1)]} = 65.47$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,244} = 3.00$ (Table A-4, Neter and Wasserman, 1974:812)

Since 65.47 >>3.00, the null hypothesis is rejected and the conclusion is demands/ maintenance actions is linearly related to at least one of the predictor variables.

Now, the test to determine if additional carriers can improve the reduced model:

Unweighted Least Squares Linear Regression of Demands (Full Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	1.59691	0.3924
CUMFH	-0.02601	0.3572
NSORT	0.08691	0.1095
CUMFH2	-1.743E-05	0.8130
NSORT2	-4.475E-05	0.9108
CUMFHNSORT	1.603E-05	0.6335

R-Squared: 0.3546; Adjusted R-Squared: 0.3412
Sum of Squares Error (SSE2): 6581.36; Residual Mean Square (MSE2): 27.3086

Hypothesis Testing:

Ho: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$ (reduced model)
Ha: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$ (full model)
The number of points, n, = 247
The number of regressors in full model, k, = 5; therefore (n-(k+1)) = 247 - 6 = 241

The number of additional regressor variables, p, = 3

Test Statistic Value: $f = \frac{(SSE1 - SSE2)/p}{MSE2} = \frac{(6636.40 - 6581.36)/3}{27.3086} = 0.672$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,241} = 2.60$ (Table A-4, Neter and Wasserman, 1974:812)

Since 0.672 < 2.60, the decision is to accept the null hypothesis and conclude additional variables do not contribute to the model. Therefore, the reduced model will be used to calculate a residual.

Based on p-values for the reduced model, the CUMFH and NSORT predictor variables contribute to the reduced model (the p-values are approximately equal to or less than $\alpha = 0.05$). The reduced model takes the following form: $Y = -0.01133x_1 + 0.10203x_2$. Y represents the expected number of demands or maintenance actions. x_1 represents cumulative flying hours and x_2 represents the number of sorties.

<u>Residual computation</u>: The cumulative flying hour total from the 1994 validation data set is 60,254.5 and the total number of sorties is 38,666. Substituting these values into the reduced model yields $Y = -0.01133(60{,}254.5) + 0.10203(38{,}666) = 3{,}262.41$ or approximately 3,262 expected demands or maintenance actions for 60,254.5 flying hours and 38,666 sorties. The actual number of 74 demands or maintenance actions from the 1994 data is 3,710. Therefore, the residual on the reduced multiple regression model is 3,710 - 3,262 = 448.

Reduced and Full Model Multiple Regressions and Hypothesis Testing for Two Digit Work Unit Code 76:

Unweighted Least Squares Linear Regression of Demands (Reduced Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	0.52078	0.3368
CUMFH	0.01797	0.0000
NSORT	-7.182E-04	0.9076

R- Squared: 0.2522; Adjusted R-Squared: 0.2461; Sum of Squares Error (SSE1): 1841.95

Hypothesis Testing: Ho: $\beta_1 = \beta_2 = ... = \beta_k = 0$

Ha: at least one $\beta_i \neq 0$ (i = 1,.......,k)

$R^2 = 0.2522$
n = number of data points = 247
k = number of carriers = 2

Test Statistic Value: $f = \dfrac{R^2 / k}{(1-R^2)/[n-(k+1)]} = \dfrac{0.2522/2}{(1-0.2522)/[247-(2+1)]} = 41.15$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,244} = 3.00$ (Table A-4, Neter and Wasserman, 1974:812)

Since 41.15 >>3.00, the null hypothesis is rejected and the conclusion is demands/ maintenance actions is linearly related to at least one of the predictor variables.

Now, the test to determine if additional carriers can improve the reduced model:

Unweighted Least Squares Linear Regression of Demands (Full Model)

Predictor Variables	Coefficient	P-Value
CONSTANT	0.20846	0.8323
CUMFH	0.01202	0.4202
NSORT	0.01442	0.6141
CUMFH2	-3.514E-05	0.3664
NSORT2	-2.095E-04	0.3207
CUMFHNSORT	1.785E-04	0.3149

R-Squared: 0.2556; Adjusted R-Squared: 0.2402
Sum of Squares Error (SSE2): 1833.54; Residual Mean Square (MSE2): 7.60804

Hypothesis Testing:

Ho: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$ (reduced model)
Ha: model is $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 + \varepsilon$ (full model)
The number of points, n, = 247
The number of regressors in full model, k, = 5; therefore (n-(k+1)) = 247 - 6 = 241

The number of additional regressor variables, p, = 3

Test Statistic Value: $f = \dfrac{(SSE1 - SSE2)/p}{MSE2} = \dfrac{(1841.95 - 1833.54)/3}{7.60804} = 0.36$

Rejection region for a level $\alpha = 0.05$ test = $f \geq F_{\alpha,k,n-(k+1)} = f \geq F_{0.05,2,241} = 2.60$ (Table A-4, Neter and Wasserman, 1974:812)

Since 0.36 < 2.60, the decision is to accept the null hypothesis and conclude additional variables do not contribute to the model. Therefore, the reduced model will be used to calculate a residual.

Based on p-values for the reduced model, only the CUMFH predictor variable contributes to the reduced model (the p-value is less than $\alpha = 0.05$). The reduced model takes the following form: $Y = 0.01797x_1$. Y represents the expected number of demands or maintenance actions and x_1 represents cumulative flying hours.

Residual computation: The cumulative flying hour total from the 1994 validation data set is 60,254.5 and the total number of sorties is 38,666. Substituting these values into the reduced model yields $Y = 0.01797(60{,}254.5) = 1{,}082.77$ or approximately 1,083 expected demands or maintenance actions for 60,254.5 flying hours and 38,666 sorties. The actual number of 76 demands or maintenance actions from the 1994 data is 1,842. Therefore, the residual on the reduced multiple regression model is 1,842 - 1,083 = 759.

Appendix E: Poisson Regression Results and Residual Calculations

Results for Two-Digit Work Unit Code Level 11:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.33647	0.0282
CUMFH	0.00146	0.0283

Deviance: 412.07; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.98256	0.0000
NSORT	0.00691	0.0000

Deviance: 396.26; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.99760	0.0000
CUMFH	-0.00219	0.0766
NSORT	0.01027	0.0000

Deviance: 392.74; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, both CONSTANT and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -0.99760 + 0.01027(38{,}666) = 396.12$ or approximately 396 expected demands/ maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 11 demands/ maintenance actions is 396. The actual number of 11 demands/maintenance actions from the 1994 data set is 794. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 794 - 396 = 398.

Poisson Regression Results for Two-Digit Work Unit Code Level 12:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.98685	0.0000
CUMFH	0.00191	0.0250

Deviance: 340.55; P-Value: 0.0001

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.256	0.0000
NSORT	0.01180	0.0000

Deviance: 312.95; P-Value: 0.0022

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.28723	0.0000
CUMFH	-0.00546	0.0066
NSORT	0.01998	0.0000

Deviance: 302.94; P-Value: 0.0061

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -2.28723 - 0.00546(60{,}254.5) + 0.01998(38{,}666) = 441.27$ or approximately 441 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 12 demands/ maintenance actions is 441. The actual number of 12 demands/maintenance actions from the 1994 data set is 318. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 318 - 441 = -123.

Poisson Regression Results for Two-Digit Work Unit Code Level 13:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	1.62039	0.0000
CUMFH	0.00111	0.0000

Deviance: 658.90; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.88507	0.0000
NSORT	0.00702	0.0000

Deviance: 537.38; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.86609	0.0000
CUMFH	-0.00363	0.0000
NSORT	0.01250	0.0000

Deviance: 482.11; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = 0.86609 - 0.00363(60{,}254.5) + 0.01250(38{,}666) = 265.47$ or approximately 265 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 13 demands/ maintenance actions is 265. The actual number of 13 demands/maintenance actions from the 1994 data set is 2,092. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 2,092 - 265 = 1,827.

Poisson Regression Results for Two-Digit Work Unit Code Level 14:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.13736	0.3081
CUMFH	5.189E-04	0.3966

Deviance: 493.65; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.55521	0.0049
NSORT	0.00588	0.0000

Deviance: 474.59; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.57246	0.0040
CUMFH	-0.00481	0.0003
NSORT	0.01303	0.0000

Deviance: 457.61; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -0.57246 - 0.00481(60{,}254.5) + 0.01303(38{,}666) = 213.42$ or approximately 213 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 14 demands/ maintenance actions is 213. The actual number of 14 demands/maintenance actions from the 1994 data set is 1,121. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 1,121 - 213 = 908.

Poisson Regression Results for Two-Digit Work Unit Code Level 23:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	1.00816	0.0000
CUMFH	0.00202	0.0000

Deviance: 557.00; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.27268	0.0176
NSORT	0.00835	0.0000

Deviance: 470.06; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.25923	0.0244
CUMFH	-0.00158	0.0047
NSORT	0.01080	0.0000

Deviance: 461.35; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = 0.25923 - 0.00158(60{,}254.5) + 0.01080(38{,}666) = 322.65$ or approximately 323 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 23 demands/ maintenance actions is 323. The actual number of 23 demands/maintenance actions from the 1994 data set is 2,069. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 2,069 - 323 = 1,746.

Poisson Regression Results for Two-Digit Work Unit Code Level 24:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.38121	0.0005
CUMFH	0.00131	0.0059

Deviance: 572.59; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.25395	0.1210
NSORT	0.00661	0.0000

Deviance: 542.59; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.26952	0.1013
CUMFH	-0.00243	0.0068
NSORT	0.01033	0.0000

Deviance: 534.23; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CUMFH and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -0.00243(60{,}254.5) + 0.01033(38{,}666) = 253.00$ or approximately 253 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 24 demands/ maintenance actions is 253. The actual number of 24 demands/maintenance actions from the 1994 data set is 1,114. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 1,114 - 253 = 861.

Poisson Regression Results for Two-Digit Work Unit Code Level 41:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.30292	0.0243
CUMFH	0.00243	0.0000

Deviance: 450.63; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.81418	0.0001
NSORT	0.00740	0.0000

Deviance: 438.33; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.81099	0.0001
CUMFH	2.867E-04	0.7492
NSORT	0.00694	0.0005

Deviance: 438.23; P-Value: 0.0000

<u>Estimation of Demands/Maintenance Actions</u>: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is:

$\hat{\mu} = -0.81099 + 0.00694(38{,}666) = 267.53$ or approximately 268 expected demands/ maintenance actions.

<u>Calculation of the Poisson Regression Residual</u>: The expected number of 41 demands/ maintenance actions is 268. The actual number of 41 demands/maintenance actions from the 1994 data set is 667. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 667 - 268 = 399.

Poisson Regression Results for Two-Digit Work Unit Code Level 42:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.22441	0.0966
CUMFH	0.00206	0.0003

Deviance: 507.57; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.87985	0.0000
NSORT	0.00786	0.0000

Deviance: 486.57; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.88941	0.0000
CUMFH	-0.00106	0.2874
NSORT	0.00951	0.0000

Deviance: 485.37; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is:

$\hat{\mu} = -0.88941 + 0.00951(38{,}666) = 366.82$ or approximately 367 expected demands/ maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 42 demands/ maintenance actions is 367. The actual number of 42 demands/maintenance actions from the 1994 data set is 766. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 766 - 367 = 399.

Poisson Regression Results for Two-Digit Work Unit Code Level 44:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.37666	0.0005
CUMFH	0.00138	0.0037

Deviance: 464.08; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.40250	0.0157
NSORT	0.00771	0.0000

Deviance: 421.76; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.42207	0.0117
CUMFH	-0.00331	0.0005
NSORT	0.01273	0.0000

Deviance: 407.13; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -0.42207 - 0.00331(60{,}254.5) + 0.01273(38{,}666) = 292.35$ or approximately 292 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 44 demands/ maintenance actions is 292. The actual number of 44 demands/maintenance actions from the 1994 data set is 665. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 665 - 292 = 373.

Poisson Regression Results for Two-Digit Work Unit Code Level 45:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.76796	0.0000
CUMFH	0.00235	0.0010

Deviance: 350.79; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-1.60279	0.0000
NSORT	0.00952	0.0000

Deviance: 331.30; P-Value: 0.0002

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-1.61624	0.0000
CUMFH	-0.00143	0.2622
NSORT	0.01175	0.0000

Deviance: 329.95; P-Value: 0.0002

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -1.61624 + 0.01175(38{,}666) = 452.71$ or approximately 453 expected demands/ maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 45 demands/ maintenance actions is 453. The actual number of 45 demands/maintenance actions from the 1994 data set is 965. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 965 - 453 = 512.

Poisson Regression Results for Two-Digit Work Unit Code Level 46:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.73428	0.0000
CUMFH	0.00407	0.0000

Deviance: 360.49; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-1.32260	0.0000
NSORT	0.01049	0.0000

Deviance: 359.30; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-1.27776	0.0000
CUMFH	0.00245	0.0012
NSORT	0.00638	0.0013

Deviance: 350.02; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -1.27776 + 0.00245(60{,}254.5) + 0.00638(38{,}666) = 393.03$ or approximately 393 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 46 demands/ maintenance actions is 393. The actual number of 46 demands/maintenance actions from the 1994 data set is 808. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 808 - 393 = 415.

Poisson Regression Results for Two-Digit Work Unit Code Level 47:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-1.15019	0.0000
CUMFH	0.00257	0.0020

Deviance: 314.66; P-Value: 0.0018

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.33310	0.0000
NSORT	0.01217	0.0000

Deviance: 289.9; P-Value: 0.0258

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.35765	0.0000
CUMFH	-0.00280	0.0887
NSORT	0.01649	0.0000

Deviance: 286.50; P-Value: 0.0320

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is:

$\hat{\mu} = -2.35765 + 0.01649(38{,}666) = 635.24$ or approximately 635 expected demands/ maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 47 demands/ maintenance actions is 635. The actual number of 47 demands/maintenance actions from the 1994 data set is 280. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 280 - 635 = -355.

Poisson Regression Results for Two-Digit Work Unit Code Level 49:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.05009	0.0000
CUMFH	0.00211	0.1333

Deviance: 196.69; P-Value: 0.9897

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.89330	0.0000
NSORT	0.00922	0.0086

Deviance: 191.46; P-Value: 0.9952

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.91000	0.0000
CUMFH	-0.00199	0.4460
NSORT	0.01231	0.0198

Deviance: 190.81; P-Value: 0.9950

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is:

$\hat{\mu} = -2.91000 + 0.01231(38{,}666) = 473.07$ or approximately 473 expected demands/ maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 49 demands/ maintenance actions is 473. The actual number of 49 demands/maintenance actions from the 1994 data set is 118. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 118 - 473 = -355.

Poisson Regression Results for Two-Digit Work Unit Code Level 51:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.56724	0.0000
CUMFH	0.00260	0.0000

Deviance: 456.33; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.01529	0.9091
NSORT	0.00817	0.0000

Deviance: 417.93; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.01243	0.9261
CUMFH	2.477E-04	0.6616
NSORT	0.00777	0.0000

Deviance: 417.74; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, only NSORT contributes to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is:

$\hat{\mu} = 0.00777(38{,}666) = 300.43$ or approximately 300 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 51 demands/ maintenance actions is 300. The actual number of 51 demands/maintenance actions from the 1994 data set is 1,043. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 1,043 - 300 = 743.

Poisson Regression Results for Two-Digit Work Unit Code Level 52:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.73840	0.0000
CUMFH	0.00209	0.0044

Deviance: 431.70; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-1.17689	0.0000
NSORT	0.00638	0.0003

Deviance: 425.82; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-1.17567	0.0000
CUMFH	1.069E-04	0.9281
NSORT	0.00621	0.0164

Deviance: 425.81; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is:

$\hat{\mu} = -1.17567 + 0.00621(38{,}666) = 238.94$ or approximately 239 expected demands/ maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 52 demands/ maintenance actions is 239. The actual number of 52 demands/maintenance actions from the 1994 data set is 284. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 284 - 239 = 45.

Poisson Regression Results for Two-Digit Work Unit Code Level 55:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.31020	0.0686
CUMFH	4.255E-04	0.5838

Deviance: 513.65; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.97823	0.0001
NSORT	0.00557	0.0010

Deviance: 502.07; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.99483	0.0001
CUMFH	-0.00483	0.0042
NSORT	0.01274	0.0000

Deviance: 492.14; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -0.99483 - 0.00483(60{,}254.5) + 0.01274(38{,}666) = 200.58$ or approximately 201 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 55 demands/ maintenance actions is 201. The actual number of 55 demands/maintenance actions from the 1994 data set is 502. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 502 - 201 = 301.

Poisson Regression Results for Two-Digit Work Unit Code Level 57:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-1.11911	0.0003
CUMFH	-0.00147	0.3369

Deviance: 223.38; P-Value: 0.8356

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.04007	0.0000
NSORT	0.00478	0.1133

Deviance: 221.77; P-Value: 0.8541

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-2.01050	0.0000
CUMFH	-0.01882	0.0008
NSORT	0.03074	0.0001

Deviance: 202.70; P-Value: 0.9748

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -2.01050 - 0.01882(60{,}254.5) + 0.03074(38{,}666) = 52.59$ or approximately 53 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 57 demands/ maintenance actions is 53. The actual number of 57 demands/maintenance actions from the 1994 data set is 265. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 265 - 53 = 212.

Poisson Regression Results for Two-Digit Work Unit Code Level 63:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.67209	0.0000
CUMFH	0.00212	0.0000

Deviance: 526.33; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.15134	0.2663
NSORT	0.00910	0.0000

Deviance: 449.66; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.16718	0.2211
CUMFH	-0.00186	0.0050
NSORT	0.01199	0.0000

Deviance: 440.93; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CUMFH and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -0.00186(60{,}254.5) + 0.01199(38{,}666) = 351.53$ or approximately 352 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 63 demands/ maintenance actions is 352. The actual number of 63 demands/maintenance actions from the 1994 data set is 1,057. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 1,057 - 352 = 705.

Poisson Regression Results for Two-Digit Work Unit Code Level 65:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.37084	0.0001
CUMFH	0.00278	0.0000

Deviance: 542.55; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.00384	0.9784
NSORT	0.00700	0.0000

Deviance: 535.90; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.01481	0.9167
CUMFH	0.00141	0.0126
NSORT	0.00470	0.0005

Deviance: 530.10; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CUMFH and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = 0.00141(60{,}254.5) + 0.00470(38{,}666) = 266.69$ or approximately 267 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 65 demands/maintenance actions is 267. The actual number of 65 demands/maintenance actions from the 1994 data set is 771. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 771 - 267 = 504.

Poisson Regression Results for Two-Digit Work Unit Code Level 71:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.38012	0.0001
CUMFH	0.00249	0.0000

Deviance: 546.29; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.21951	0.1400
NSORT	0.00812	0.0000

Deviance: 512.32; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.21961	0.1403
CUMFH	-9.668E-06	0.9880
NSORT	0.00813	0.0000

Deviance: 512.32; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, only NSORT contributes to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is:

$\hat{\mu} = 0.00813(38{,}666) = 314.35$ or approximately 314 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 71 demands/ maintenance actions is 314. The actual number of 71 demands/maintenance actions from the 1994 data set is 1,049. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 1,049 - 314 = 735.

Poisson Regression Results for Two-Digit Work Unit Code Level 74:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	1.90619	0.0000
CUMFH	0.00226	0.0000

Deviance: 840.81; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	1.19240	0.0000
NSORT	0.00855	0.0000

Deviance: 628.75; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	1.18292	0.0000
CUMFH	-9.924E-04	0.0027
NSORT	0.001011	0.0000

Deviance: 619.26; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = 1.18292 - 0.0009924(60{,}254.5) + 0.001011(38{,}666) = 332.29$ or approximately 332 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 74 demands/ maintenance actions is 332. The actual number of 74 demands/maintenance actions from the 1994 data set is 3,710. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 3,710 - 332 = 3,378.

Poisson Regression Results for Two-Digit Work Unit Code Level 75:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.54251	0.0000
CUMFH	4.454E-04	0.3783

Deviance: 566.99; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.11038	0.4940
NSORT	0.00549	0.0000

Deviance: 542.15; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.12693	0.4345
CUMFH	-0.00462	0.0000
NSORT	0.01237	0.0000

Deviance: 518.77; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is:
$\hat{\mu} = -0.00462(60{,}254.5) + 0.01237(38{,}666) = 199.92$ or approximately 200 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 75 demands/ maintenance actions is 200. The actual number of 75 demands/maintenance actions from the 1994 data set is 725. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 725 - 200 = 525.

Poisson Regression Results for Two-Digit Work Unit Code Level 76:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.60785	0.0000
CUMFH	0.00360	0.0000

Deviance: 489.07; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.35741	0.0020
NSORT	0.00742	0.0000

Deviance: 528.86; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	0.40819	0.0004
CUMFH	0.00295	0.0000
NSORT	0.00247	0.0203

Deviance: 483.65; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = 0.40819 + 0.00295(60{,}254.5) + 0.00247(38{,}666) = 273.66$ or approximately 274 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 76 demands/ maintenance actions is 274. The actual number of 76 demands/maintenance actions from the 1994 data set is 1,842. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 1,842 - 274 = 1,568.

Poisson Regression Results for Two-Digit Work Unit Code Level 97:

CUMFH Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.34314	0.06011
CUMFH	-9.601E-05	0.9106

Deviance: 482.82; P-Value: 0.0000

NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.91677	0.0004
NSORT	0.00415	0.0205

Deviance: 477.31; P-Value: 0.0000

CUMFH and NSORT Model Results:

Predictor Variables	Coefficient	p-value
CONSTANT	-0.93006	0.0003
CUMFH	-0.00552	0.0056
NSORT	0.01186	0.0002

Deviance: 467.16; P-Value: 0.0000

Estimation of Demands/Maintenance Actions: The general form of the Poisson regression model used in this study is: $\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$. Based on the deviance values, the CUMFH and NSORT model has the smallest deviance. Predictor variable p-values will be compared to an $\alpha = 0.05$ to determine which variables contribute to the model. In the CUMFH and NSORT model, CONSTANT, CUMFH, and NSORT contribute to the model. This model will be used to estimate the number of demands/maintenance actions from the 1994 validation data set. The 1994 validation data set is based on 60,254.5 flying hours and 38,666 sorties. The expected number of maintenance actions is: $\hat{\mu} = -0.93006 - 0.00552(60{,}254.5) + 0.01186(38{,}666) = 143.12$ or approximately 143 expected demands/maintenance actions.

Calculation of the Poisson Regression Residual: The expected number of 97 demands/ maintenance actions is 143. The actual number of 97 demands/maintenance actions from the 1994 data set is 476. The residual is calculated by taking the actual value minus the expected value. The value of the residual is 476 - 143 = 333.

Appendix F: Data Tables and Poisson Process Calculations

Table F-1: 1993 Data Used to Determine Poisson Process Lambdas

Two-Digit Work Unit Code	Number of Maint. Actions	Cum. Flying Hours	Cum. # of Sorties	Lambda, λ, (# of Maint. Actions/ Cum Flying Hours)	Lambda, λ, (# of Maint. Actions/ Cum # of Sorties)
11	237	48,337.5	32,057	0.0049	0.0074
12	136	48,337.5	32,057	0.0028	0.0042
13	1,560	48,337.5	32,057	0.0323	0.0487
14	314	48,337.5	32,057	0.0065	0.0098
23	1,023	48,337.5	32,057	0.0212	0.0319
24	471	48,337.5	32,057	0.0097	0.0147
41	301	48,337.5	32,057	0.0062	0.0094
42	301	48,337.5	32,057	0.0062	0.0094
44	475	48,337.5	32,057	0.0098	0.0148
45	186	48,337.5	32,057	0.0038	0.0058
46	284	48,337.5	32,057	0.0058	0.0088
47	133	48,337.5	32,057	0.0028	0.0041
49	49	48,337.5	32,057	0.0010	0.0015
51	747	48,337.5	32,057	0.0155	0.0233
52	181	48,337.5	32,057	0.0037	0.0056
55	197	48,337.5	32,057	0.0041	0.0061
57	61	48,337.5	32,057	0.0013	0.0019
63	747	48,337.5	32,057	0.0155	0.0233
65	639	48,337.5	32,057	0.0132	0.0199
71	605	48,337.5	32,057	0.0125	0.0189
74	2,643	48,337.5	32,057	0.0547	0.0824
75	464	48,337.5	32,057	0.0096	0.0145
76	974	48,337.5	32,057	0.0201	0.0304
97	172	48,337.5	32,057	0.0036	0.0054

Note: Data used to comprise the above table was for F-15Cs covering the period of May to December 1993. Database contained 247 aircraft which flew a total of 32,057 sorties and accumulated 48,337.5 flying hours over the eight month period.

How to interpret table: Consider two digit work unit code, 11. The 247 aircraft in the database had 237 maintenance actions at the 11 work unit code level, while flying 48,337.5 hours or 32,057 sorties.

Table F-2: 1994 Validation Data

Two-Digit Work Unit Code	Number of Actual Maintenance Actions	Cum. Flying Hours	Cum. # of Sorties
11	794	60,254.5	38,666
12	318	60,254.5	38,666
13	2,092	60,254.5	38,666
14	1,121	60,254.5	38,666
23	2,069	60,254.5	38,666
24	1,114	60,254.5	38,666
41	667	60,254.5	38,666
42	766	60,254.5	38,666
44	665	60,254.5	38,666
45	965	60,254.5	38,666
46	808	60,254.5	38,666
47	280	60,254.5	38,666
49	118	60,254.5	38,666
51	1,043	60,254.5	38,666
52	284	60,254.5	38,666
55	502	60,254.5	38,666
57	265	60,254.5	38,666
63	1,057	60,254.5	38,666
65	771	60,254.5	38,666
71	1,049	60,254.5	38,666
74	3,710	60,254.5	38,666
75	725	60,254.5	38,666
76	1,842	60,254.5	38,666
97	476	60,254.5	38,666

Note: Data used to comprise the above table was for F-15Cs covering the period from of February to June 1994. Database contained 340 aircraft which flew a total of 38,666 sorties and accumulated 60,254.5 flying hours over the five month period.

How to interpret table: Consider work unit code 11. The 340 aircraft in the database had 794 maintenance actions at the 11 work unit code level, while flying 60,254.5 flying hours or 38,666 sorties.

<u>Poisson Process Calculations for the 11 Work Unit Code Level</u>:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties.
Thus, Z is Poisson (0.0049) based on flying hours [237/48,337.5 = 0.0049].
Z is Poisson (0.0074) based on sorties [237/32,057 = 0.0074].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

<u>Flying Hour Based</u>:
If X is approximately Poisson (0.0049 * 60,254.5), the expected value of X is (0.0049)(60,254.5) = 295.247. Also, the variance of X is 295.247, while the standard deviation, σ, is $\sqrt{295.247} = 17.18$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (260, 329).

The probability that $(X \leq 260 \text{ or } X \geq 329) = 0.01999 + (1 - 0.97536) = 0.04463$.

The <u>actual</u> number of 11 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 794. The <u>expected</u> number of 11 maintenance actions is approximately 295. Thus, the residual on the Poisson process based on flying hours is 794 - 295 = 499.

<u>Sortie Based</u>:
If X is approximately Poisson (0.0074 * 38,666), the expected value of X is (0.0074)(38,666) = 286.128. Also, the variance of X is 286.128, while the standard deviation, σ, is $\sqrt{286.128} = 16.91$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (252, 320).

The probability that $(X \leq 252 \text{ or } X \geq 320) = 0.02175 + (1 - 0.9774) = 0.04435$.

The <u>actual</u> number of 11 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 794. The <u>expected</u> number of 11 maintenance actions is approximately 286. Thus, the residual on the Poisson process based on sorties is 794 - 286 = 508.

<u>**Poisson Process Calculations for the 12 Work Unit Code Level**</u>:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties.
Thus, Z is Poisson (0.0028) based on flying hours [136/48,337.5 = 0.0028].
Z is Poisson (0.0042) based on sorties [136/32,057 = 0.0042].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

<u>Flying Hour Based</u>:
If X is approximately Poisson (0.0028 * 60,254.5), the expected value of X is (0.0028)(60,254.5) = 168.713. Also, the variance of X is 168.713, while the standard deviation, σ, is $\sqrt{168.713} = 12.99$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (143, 195).

The probability that ($X \leq 143$ or $X \geq 195$) = 0.02388 + (1-0.97849) = 0.04539.

The <u>actual</u> number of 12 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 318. The <u>expected</u> number of 11 maintenance actions is approximately 169. Thus, the residual on the Poisson process based on flying hours is 318 - 169 = 149.

<u>Sortie Based</u>:
If X is approximately Poisson (0.0042 * 38,666), the expected value of X is (0.0042)(38,666) = 162.397. Also, the variance of X is 162.397, while the standard deviation, σ, is $\sqrt{162.397} = 12.74$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (137, 188).

The probability that ($X \leq 137$ or $X \geq 188$) = 0.02310 + (1 - 0.97776) = 0.04534.

The <u>actual</u> number of 12 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 318. The <u>expected</u> number of 11 maintenance actions is approximately 162. Thus, the residual on the Poisson process based on sorties is 318 - 162 = 156.

Poisson Process Calculations for the 13 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0323) based on flying hours [1,560/48,337.5 = 0.0323].
Z is Poisson (0.0487) based on sorties [1,560/32,057 = 0.0487].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0323 * 60,254.5), the expected value of X is (0.0323)(60,254.5) = 1,946.220. Also, the variance of X is 1,946.220, while the standard deviation, σ, is $\sqrt{1{,}946.220} = 44.12$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (1,858, 2,034).

The probability that $(X \leq 1{,}858 \text{ or } X \geq 2{,}034) = 0.02276 + (1-0.9767) = 0.04606$.

The actual number of 13 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 2,092. The expected number of 13 maintenance actions is approximately 1,946. Thus, the residual on the Poisson process based on flying hours is 2,092 - 1,946 = 146.

Sortie Based:
If X is approximately Poisson (0.0487 * 38,666), the expected value of X is (0.0487)(38,666) = 1,883.034. Also, the variance of X is 1,883.034, while the standard deviation, σ, is $\sqrt{1{,}883.034} = 43.39$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (1,796, 1,970).

The probability that $(X \leq 1{,}796 \text{ or } X \geq 1{,}970) = 0.02244 + (1 - 0.97747) = 0.04497$.

The actual number of 13 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 2,092. The expected number of 13 maintenance actions is approximately 1,883. Thus, the residual on the Poisson process based on sorties is 2,092 - 1,883 = 209.

Poisson Process Calculations for the 14 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0065) based on flying hours [314/48,337.5 = 0.0065].
Z is Poisson (0.0098) based on sorties [314/32,057 = 0.0098].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0065 * 60,254.5), the expected value of X is (0.0065)(60,254.5) = 391.654 Also, the variance of X is 391.654, while the standard deviation, σ, is $\sqrt{391.654} = 19.79$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (352,431).

The probability that ($X \leq 352$ or $X \geq 431$) = 0.02252 + (1-0.97664) = 0.04588.

The actual number of 14 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 1,121. The expected number of 14 maintenance actions is approximately 392. Thus, the residual on the Poisson process based on flying hours is 1,121 - 392 = 729.

Sortie Based:
If X is approximately Poisson (0.0098 * 38,666), the expected value of X is (0.0098)(38,666) = 378.927. Also, the variance of X is 378.927, while the standard deviation, σ, is $\sqrt{378.927} = 19.47$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (340,418).

The probability that ($X \leq 340$ or $X \geq 418$) = 0.02274 + (1 - 0.97764) = 0.0451.

The actual number of 14 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 1,121. The expected number of 14 maintenance actions is approximately 379. Thus, the residual on the Poisson process based on sorties is 1,121 - 379 = 742.

Poisson Process Calculations for the 23 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0212) based on flying hours [1,023/48,337.5 = 0.0212].
Z is Poisson (0.0319) based on sorties [1,023/32,057 = 0.0319].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0212 * 60,254.5), the expected value of X is (0.0212)(60,254.5) = 1,277.395 Also, the variance of X is 1,277.395, while the standard deviation, σ, is $\sqrt{1{,}277.395} = 35.74$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (1,206,1,349).

The probability that ($X \leq 1{,}206$ or $X \geq 1{,}349$) = 0.02288 + (1-0.97744) = 0.04544.

The actual number of 23 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 2,069. The expected number of 23 maintenance actions is approximately 1,277. Thus, the residual on the Poisson process based on flying hours is 2,069 - 1,277 = 792.

Sortie Based:
If X is approximately Poisson (0.0319 * 38,666), the expected value of X is (0.0319)(38,666) = 1,233.445. Also, the variance of X is 1,233.445, while the standard deviation, σ, is $\sqrt{1{,}233.445} = 35.12$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (1,163,1,304).

The probability that ($X \leq 1{,}163$ or $X \geq 1{,}304$) = 0.02243 + (1 - 0.97773) = 0.0447.

The actual number of 23 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 2,069. The expected number of 23 maintenance actions is approximately 1,233. Thus, the residual on the Poisson process based on sorties is 2,069 - 1,233 = 836.

Poisson Process Calculations for the 24 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0097) based on flying hours [471/48,337.5 = 0.0097].
Z is Poisson (0.0147) based on sorties [471/32,057 = 0.0147].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0097 * 60,254.5), the expected value of X is (0.0097)(60,254.5) = 584.469. Also, the variance of X is 584.469, while the standard deviation, σ, is $\sqrt{584.469} = 24.18$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (536,633).

The probability that $(X \leq 536 \text{ or } X \geq 633) = 0.02247 + (1-0.97765) = 0.04482$.

The actual number of 24 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 1,114. The expected number of 24 maintenance actions is approximately 584. Thus, the residual on the Poisson process based on flying hours is 1,114 - 584 = 530.

Sortie Based:
If X is approximately Poisson (0.0147 * 38,666), the expected value of X is (0.0147)(38,666) = 568.390. Also, the variance of X is 568.390, while the standard deviation, σ, is $\sqrt{568.390} = 23.84$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (521,616).

The probability that $(X \leq 521 \text{ or } X \geq 616) = 0.02342 + (1 - 0.97710) = 0.04632$.

The actual number of 24 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 1,114. The expected number of 24 maintenance actions is approximately 568. Thus, the residual on the Poisson process based on sorties is 1,114 - 568 = 546.

Poisson Process Calculations for the 41 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0062) based on flying hours [301/48,337.5 = 0.0062].
Z is Poisson (0.0094) based on sorties [301/32,057 = 0.0094].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0062 * 60,254.5), the expected value of X is (0.0062)(60,254.5) = 373.578. Also, the variance of X is 373.578, while the standard deviation, σ, is $\sqrt{373.578} = 19.33$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (335,412).

The probability that $(X \leq 335 \text{ or } X \geq 412) = 0.02295 + (1-0.97663) = 0.04632$.

The actual number of 41 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 667. The expected number of 41 maintenance actions is approximately 374. Thus, the residual on the Poisson process based on flying hours is 667 - 374 = 293.

Sortie Based:
If X is approximately Poisson (0.0094 * 38,666), the expected value of X is (0.0094)(38,666) = 363.460. Also, the variance of X is 363.460, while the standard deviation, σ, is $\sqrt{363.460} = 19.06$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (325,402).

The probability that $(X \leq 325 \text{ or } X \geq 402) = 0.02177 + (1 - 0.97837) = 0.0434$.

The actual number of 41 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 667. The expected number of 41 maintenance actions is approximately 363. Thus, the residual on the Poisson process based on sorties is 667 - 363 = 304.

Poisson Process Calculations for the 42 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0062) based on flying hours [301/48,337.5 = 0.0062].
Z is Poisson (0.0094) based on sorties [301/32,057 = 0.0094].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0062 * 60,254.5), the expected value of X is (0.0062)(60,254.5) = 373.578. Also, the variance of X is 373.578, while the standard deviation, σ, is $\sqrt{373.578} = 19.33$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (335,412).

The probability that ($X \leq 335$ or $X \geq 412$) = 0.02295 + (1-0.97663) = 0.04632.

The actual number of 42 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 766. The expected number of 42 maintenance actions is approximately 374. Thus, the residual on the Poisson process based on flying hours is 766 - 374 = 392.

Sortie Based:
If X is approximately Poisson (0.0094 * 38,666), the expected value of X is (0.0094)(38,666) = 363.460. Also, the variance of X is 363.460, while the standard deviation, σ, is $\sqrt{363.460} = 19.06$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (325,402).

The probability that ($X \leq 325$ or $X \geq 402$) = 0.02177 + (1 - 0.97837) = 0.0434.

The actual number of 42 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 766. The expected number of 42 maintenance actions is approximately 363. Thus, the residual on the Poisson process based on sorties is 766 - 363 = 403.

Poisson Process Calculations for the 44 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0098) based on flying hours [475/48,337.5 = 0.0098].
Z is Poisson (0.0148) based on sorties [475/32,057 = 0.0148].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0098 * 60,254.5), the expected value of X is (0.0098)(60,254.5) = 590.494. Also, the variance of X is 590.494, while the standard deviation, σ, is $\sqrt{590.494} = 24.30$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (542,639).

The probability that ($X \leq 542$ or $X \geq 639$) = 0.02298 + (1-0.97706) = 0.04592.

The actual number of 44 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 665. The expected number of 44 maintenance actions is approximately 590. Thus, the residual on the Poisson process based on flying hours is 665 - 590 = 75.

Sortie Based:
If X is approximately Poisson (0.0148 * 38,666), the expected value of X is (0.0148)(38,666) = 572.257. Also, the variance of X is 572.257, while the standard deviation, σ, is $\sqrt{572.257} = 23.92$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (524,620).

The probability that ($X \leq 524$ or $X \geq 620$) = 0.02179 + (1 - 0.97704) = 0.04475.

The actual number of 44 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 665. The expected number of 44 maintenance actions is approximately 572. Thus, the residual on the Poisson process based on sorties is 665 - 572 = 93.

Poisson Process Calculations for the 45 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0038) based on flying hours [186/48,337.5 = 0.0038].
Z is Poisson (0.0058) based on sorties [186/32,057 = 0.0058].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0038 * 60,254.5), the expected value of X is (0.0038)(60,254.5) = 228.967. Also, the variance of X is 228.967, while the standard deviation, σ, is $\sqrt{228.967} = 15.13$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (199,259).

The probability that ($X \leq 199$ or $X \geq 259$) = 0.02384 + (1-0.97648) = 0.04736.

The actual number of 45 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 965. The expected number of 45 maintenance actions is approximately 229. Thus, the residual on the Poisson process based on flying hours is 965 - 229 = 736.

Sortie Based:
If X is approximately Poisson (0.0058 * 38,666), the expected value of X is (0.0058)(38,666) = 224.263. Also, the variance of X is 224.263, while the standard deviation, σ, is $\sqrt{224.263} = 14.98$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (194,254).

The probability that ($X \leq 194$ or $X \geq 254$) = 0.02156 + (1 - 0.97653) = 0.04503.

The actual number of 45 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 965. The expected number of 45 maintenance actions is approximately 224. Thus, the residual on the Poisson process based on sorties is 965 - 224 = 741.

<u>Poisson Process Calculations for the 46 Work Unit Code Level</u>:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0058) based on flying hours [284/48,337.5 = 0.0058].

Z is Poisson (0.0088) based on sorties [284/32,057 = 0.0088].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

<u>Flying Hour Based</u>:
If X is approximately Poisson (0.0058 * 60,254.5), the expected value of X is (0.0058)(60,254.5) = 349.476. Also, the variance of X is 349.476, while the standard deviation, σ, is $\sqrt{349.476} = 18.69$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (312,387).

The probability that ($X \leq 312$ or $X \geq 387$) = 0.02246 + (1-0.97765) = 0.04481.

The <u>actual</u> number of 46 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 808. The <u>expected</u> number of 46 maintenance actions is approximately 349. Thus, the residual on the Poisson process based on flying hours is 808 - 349 = 459.

<u>Sortie Based</u>:
If X is approximately Poisson (0.0088 * 38,666), the expected value of X is (0.0088)(38,666) = 340.261. Also, the variance of X is 340.261, while the standard deviation, σ, is $\sqrt{340.261} = 18.45$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (303,377).

The probability that ($X \leq 303$ or $X \geq 377$) = 0.02163 + (1 - 0.97684) = 0.04479.

The <u>actual</u> number of 46 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 808. The <u>expected</u> number of 46 maintenance actions is approximately 340. Thus, the residual on the Poisson process based on sorties is 808 - 340 = 468.

Poisson Process Calculations for the 47 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0028) based on flying hours [133/48,337.5 = 0.0028].
Z is Poisson (0.0041) based on sorties [133/32,057 = 0.0041].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0028 * 60,254.5), the expected value of X is (0.0028)(60,254.5) = 168.713. Also, the variance of X is 168.713, while the standard deviation, σ, is $\sqrt{168.713} = 12.99$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (143,195).

The probability that ($X \leq 143$ or $X \geq 195$) = 0.02388 + (1-0.97849) = 0.04539.

The actual number of 47 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 280. The expected number of 47 maintenance actions is approximately 169. Thus, the residual on the Poisson process based on flying hours is 280 - 169 = 111.

Sortie Based:
If X is approximately Poisson (0.0041 * 38,666), the expected value of X is (0.0041)(38,666) = 158.531. Also, the variance of X is 158.531, while the standard deviation, σ, is $\sqrt{158.531} = 12.59$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (133,184).

The probability that ($X \leq 133$ or $X \geq 184$) = 0.02116 + (1 - 0.97844) = 0.04272.

The actual number of 47 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 280. The expected number of 47 maintenance actions is approximately 158. Thus, the residual on the Poisson process based on sorties is 280 - 158 = 122.

Poisson Process Calculations for the 49 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties.
Thus, Z is Poisson (0.0010) based on flying hours [49/48,337.5 = 0.0010].
Z is Poisson (0.0015) based on sorties [49/32,057 = 0.0015].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0010 * 60,254.5), the expected value of X is (0.0010)(60,254.5) = 60.255. Also, the variance of X is 60.255, while the standard deviation, σ, is $\sqrt{60.255} = 7.76$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (45,76).

The probability that $(X \leq 45 \text{ or } X \geq 76) = 0.0247 + (1-0.97873) = 0.04597$.

The actual number of 49 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 118. The expected number of 49 maintenance actions is approximately 60. Thus, the residual on the Poisson process based on flying hours is 118 - 60 = 58.

Sortie Based:
If X is approximately Poisson (0.0015 * 38,666), the expected value of X is (0.0015)(38,666) = 57.999. Also, the variance of X is 57.999, while the standard deviation, σ, is $\sqrt{57.999} = 7.62$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (43,73).

The probability that $(X \leq 43 \text{ or } X \geq 73) = 0.02443 + (1 - 0.97582) = 0.04861$.

The actual number of 49 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 118. The expected number of 49 maintenance actions is approximately 58. Thus, the residual on the Poisson process based on sorties is 118 - 58 = 60.

Poisson Process Calculations for the 51 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties.
Thus, Z is Poisson (0.0155) based on flying hours [747/48,337.5 = 0.0155].
Z is Poisson (0.0233) based on sorties [747/32,057 = 0.0233].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0155 * 60,254.5), the expected value of X is (0.0155)(60,254.5) = 933.945. Also, the variance of X is 933.945, while the standard deviation, σ, is $\sqrt{933.945} = 30.56$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (873,995).

The probability that ($X \leq 873$ or $X \geq 995$) = 0.02306 + (1-0.97714) = 0.04592.

The actual number of 51 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 1,043. The expected number of 51 maintenance actions is approximately 934. Thus, the residual on the Poisson process based on flying hours is 1,043 - 934 = 109.

Sortie Based:
If X is approximately Poisson (0.0233 * 38,666), the expected value of X is (0.0233)(38,666) = 900.918. Also, the variance of X is 900.918, while the standard deviation, σ, is $\sqrt{900.918} = 30.02$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (841,961).

The probability that ($X \leq 841$ or $X \geq 961$) = 0.02295 + (1 - 0.97735) = 0.0456.

The actual number of 51 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 1,043. The expected number of 51 maintenance actions is approximately 901. Thus, the residual on the Poisson process based on sorties is 1,043 - 901 = 142.

Poisson Process Calculations for the 52 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0037) based on flying hours [181/48,337.5 = 0.0037].
Z is Poisson (0.0056) based on sorties [181/32,057 = 0.0056].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0037 * 60,254.5), the expected value of X is (0.0037)(60,254.5) = 222.942. Also, the variance of X is 222.942, while the standard deviation, σ, is $\sqrt{222.942} = 14.93$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (193,253).

The probability that ($X \leq 193$ or $X \geq 253$) = 0.02241 + (1-0.97795) = 0.04446.

The actual number of 52 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 284. The expected number of 52 maintenance actions is approximately 223. Thus, the residual on the Poisson process based on flying hours is 284 - 223 = 61.

Sortie Based:
If X is approximately Poisson (0.0056 * 38,666), the expected value of X is (0.0056)(38,666) = 216.530. Also, the variance of X is 216.530, while the standard deviation, σ, is $\sqrt{216.530} = 14.71$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (187,246).

The probability that ($X \leq 187$ or $X \geq 246$) = 0.02233 + (1 - 0.97742) = 0.04491.

The actual number of 52 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 284. The expected number of 52 maintenance actions is approximately 217. Thus, the residual on the Poisson process based on sorties is 284 - 217 = 67.

<u>**Poisson Process Calculations for the 55 Work Unit Code Level**</u>:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisscn (0.0041) based on flying hours [197/48,337.5 = 0.0041].
Z is Poisson (0.0061) based on sorties [197/32,057 = 0.0061].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

<u>Flying Hour Based</u>:
If X is approximately Poisson (0.0041 * 60,254.5), the expected value of X is (0.0041)(60,254.5) = 247.043. Also, the variance of X is 247.043, while the standard deviation, σ, is $\sqrt{247.043} = 15.72$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (216,278).

The probability that ($X \leq 216$ or $X \geq 278$) = 0.02416 + (1-0.97566) = 0.0485.

The <u>actual</u> number of 55 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 502. The <u>expected</u> number of 55 maintenance actions is approximately 247. Thus, the residual on the Poisson process based on flying hours is 502 - 247 = 255.

<u>Sortie Based</u>:
If X is approximately Poisson (0.0061 * 38,666), the expected value of X is (0.0061)(38,666) = 235.863. Also, the variance of X is 235.863, while the standard deviation, σ, is $\sqrt{235.863} = 15.36$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (205,267).

The probability that ($X \leq 205$ or $X \geq 267$) = 0.02218 + (1 - 0.97866) = 0.04352.

The <u>actual</u> number of 55 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 502. The <u>expected</u> number of 55 maintenance actions is approximately 236. Thus, the residual on the Poisson process based on sorties is 502 - 236 = 266.

Poisson Process Calculations for the 57 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0013) based on flying hours [61/48,337.5 = 0.0013].
Z is Poisson (0.0019) based on sorties [61/32,057 = 0.0019].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0013 * 60,254.5), the expected value of X is (0.0013)(60,254.5) = 78.331 Also, the variance of X is 78.331, while the standard deviation, σ, is $\sqrt{78.331} = 8.85$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (61,96).

The probability that ($X \leq 61$ or $X \geq 96$) = 0.02517 + (1-0.97716) = 0.04801.

The actual number of 57 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 265. The expected number of 57 maintenance actions is approximately 78. Thus, the residual on the Poisson process based on flying hours is 265 - 78 = 187.

Sortie Based:
If X is approximately Poisson (0.0019 * 38,666), the expected value of X is (0.0019)(38,666) = 73.465. Also, the variance of X is 73.465, while the standard deviation, σ, is $\sqrt{73.465} = 8.57$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (56,91).

The probability that ($X \leq 56$ or $X \geq 91$) = 0.02051 + (1 - 0.97954) = 0.04097.

The actual number of 57 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 265. The expected number of 57 maintenance actions is approximately 73. Thus, the residual on the Poisson process based on sorties is 265 - 73 = 192.

Poisson Process Calculations for the 63 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0155) based on flying hours [747/48,337.5 = 0.0155].
Z is Poisson (0.0233) based on sorties [747/32,057 = 0.0233].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0155 * 60,254.5), the expected value of X is (0.0155)(60,254.5) = 933.945. Also, the variance of X is 933.945, while the standard deviation, σ, is $\sqrt{933.945} = 30.56$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (873,995).

The probability that $(X \leq 873 \text{ or } X \geq 995) = 0.02306 + (1-0.97714) = 0.04592$.

The actual number of 63 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 1,057. The expected number of 63 maintenance actions is approximately 934. Thus, the residual on the Poisson process based on flying hours is 1,057 - 934 = 123.

Sortie Based:
If X is approximately Poisson (0.0233 * 38,666), the expected value of X is (0.0233)(38,666) = 900.918. Also, the variance of X is 900.918, while the standard deviation, σ, is $\sqrt{900.918} = 30.02$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (841,961).

The probability that $(X \leq 841 \text{ or } X \geq 961) = 0.02295 + (1 - 0.97735) = 0.0456$.

The actual number of 63 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 1,057. The expected number of 63 maintenance actions is approximately 901. Thus, the residual on the Poisson process based on sorties is 1,057 - 901 = 156.

<u>Poisson Process Calculations for the 65 Work Unit Code Level</u>:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0132) based on flying hours [639/48,337.5 = 0.0132].
Z is Poisson (0.0199) based on sorties [639/32,057 = 0.0199].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

<u>Flying Hour Based</u>:
If X is approximately Poisson (0.0132 * 60,254.5), the expected value of X is (0.0132)(60,254.5) = 795.359. Also, the variance of X is 795.359, while the standard deviation, σ, is $\sqrt{795.359} = 28.20$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (739,852).

The probability that ($X \leq 739$ or $X \geq 852$) = 0.02283 + (1-0.97770) = 0.04513.

The <u>actual</u> number of 65 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 771. The <u>expected</u> number of 65 maintenance actions is approximately 795. Thus, the residual on the Poisson process based on flying hours is 771 - 795 = 24 (by taking absolute value).

<u>Sortie Based</u>:
If X is approximately Poisson (0.0199 * 38,666), the expected value of X is (0.0199)(38,666) = 769.453. Also, the variance of X is 769.453, while the standard deviation, σ, is $\sqrt{769.453} = 27.74$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (714,825).

The probability that ($X \leq 714$ or $X \geq 825$) = 0.02279 + (1 - 0.97739) = 0.0454.

The <u>actual</u> number of 65 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 771. The <u>expected</u> number of 65 maintenance actions is approximately 769. Thus, the residual on the Poisson process based on sorties is 771 - 769 = 2.

Poisson Process Calculations for the 71 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0125) based on flying hours [605/48,337.5 = 0.0125].
Z is Poisson (0.0189) based on sorties [605/32,057 = 0.0189].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0125 * 60,254.5), the expected value of X is (0.0125)(60,254.5) = 753.181. Also, the variance of X is 753.181, while the standard deviation, σ, is $\sqrt{753.181} = 27.44$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (698,808).

The probability that $(X \leq 698 \text{ or } X \geq 808) = 0.02216 + (1-0.97713) = 0.04503$.

The actual number of 71 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 1,049. The expected number of 71 maintenance actions is approximately 753. Thus, the residual on the Poisson process based on flying hours is 1,049 - 753 = 296.

Sortie Based:
If X is approximately Poisson (0.0189 * 38,666), the expected value of X is (0.0189)(38,666) = 730.787. Also, the variance of X is 730.787, while the standard deviation, σ, is $\sqrt{730.787} = 27.03$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (677,785).

The probability that $(X \leq 677 \text{ or } X \geq 785) = 0.02332 + (1 - 0.97754) = 0.04578$.

The actual number of 71 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 1,049. The expected number of 71 maintenance actions is approximately 731. Thus, the residual on the Poisson process based on sorties is 1,049 - 731 = 318.

<u>Poisson Process Calculations for the 74 Work Unit Code Level</u>:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0547) based on flying hours [2,643/48,337.5 = 0.0547].
Z is Poisson (0.0824) based on sorties [2,643/32,057 = 0.0824].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

<u>Flying Hour Based</u>:
If X is approximately Poisson (0.0547 * 60,254.5), the expected value of X is (0.0547)(60,254.5) = 3,295.921. Also, the variance of X is 3,295.921, while the standard deviation, σ, is $\sqrt{3295.921} = 57.41$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (3,181,3,411).

The probability that ($X \leq 3{,}181$ or $X \geq 3{,}411$) = 0.02265 + (1-0.97749) = 0.04516.

The <u>actual</u> number of 74 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 3,710. The <u>expected</u> number of 74 maintenance actions is approximately 3,296. Thus, the residual on the Poisson process based on flying hours is 3,710 - 3,296 = 414.

<u>Sortie Based</u>:
If X is approximately Poisson (0.0824 * 38,666), the expected value of X is (0.0824)(38,666) = 3,186.078. Also, the variance of X is 3,186.078, while the standard deviation, σ, is $\sqrt{3{,}186.078} = 56.45$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (3,073,3,299).

The probability that ($X \leq 3{,}073$ or $X \geq 3{,}299$) = 0.02257 + (1 - 0.97728) = 0.04529.

The <u>actual</u> number of 74 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 3,710. The <u>expected</u> number of 74 maintenance actions is approximately 3,186. Thus, the residual on the Poisson process based on sorties is 3,710 - 3,186 = 524.

Poisson Process Calculations for the 75 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0096) based on flying hours [464/48,337.5 = 0.0096].
Z is Poisson (0.0145) based on sorties [464/32,057 = 0.0145].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0096 * 60,254.5), the expected value of X is (0.0096)(60,254.5) = 578.443. Also, the variance of X is 578.443, while the standard deviation, σ, is $\sqrt{578.443} = 24.05$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (530,627).

The probability that ($X \leq 530$ or $X \geq 627$) = 0.02196 + (1-0.97824) = 0.04372.

The actual number of 75 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 725. The expected number of 75 maintenance actions is approximately 578. Thus, the residual on the Poisson process based on flying hours is 725 - 578 = 147.

Sortie Based:
If X is approximately Poisson (0.0145 * 38,666), the expected value of X is (0.0145)(38,666) = 560.657. Also, the variance of X is 560.657, while the standard deviation, σ, is $\sqrt{560.657} = 23.68$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (513,608).

The probability that ($X \leq 513$ or $X \geq 608$) = 0.02204 + (1 - 0.97723) = 0.04481.

The actual number of 75 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 725. The expected number of 75 maintenance actions is approximately 561. Thus, the residual on the Poisson process based on sorties is 725 - 561 = 164.

Poisson Process Calculations for the 76 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0201) based on flying hours [974/48,337.5 = 0.0201].
Z is Poisson (0.0304) based on sorties [974/32,057 = 0.0304].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0201 * 60,254.5), the expected value of X is (0.0201)(60,254.5) = 1,211.115. Also, the variance of X is 1,211.115, while the standard deviation, σ, is $\sqrt{1{,}211.115} = 34.80$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (1,142,1,281).

The probability that ($X \leq 1{,}142$ or $X \geq 1{,}281$) = 0.02352 + (1-0.97768) = 0.04584.

The actual number of 76 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 1,842. The expected number of 76 maintenance actions is approximately 1,211. Thus, the residual on the Poisson process based on flying hours is 1,842 - 1,211 = 631.

Sortie Based:
If X is approximately Poisson (0.0304 * 38,666), the expected value of X is (0.0304)(38,666) = 1,175.446. Also, the variance of X is 1,175.446, while the standard deviation, σ, is $\sqrt{1{,}175.446} = 34.28$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (1,107,1,244).

The probability that ($X \leq 1{,}107$ or $X \geq 1{,}244$) = 0.02294 + (1 - 0.97723) = 0.04571.

The actual number of 76 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 1,842. The expected number of 76 maintenance actions is approximately 1,175. Thus, the residual on the Poisson process based on sorties is 1,842 - 1,175 = 667.

Poisson Process Calculations for the 97 Work Unit Code Level:

Let Z be the number of maintenance actions in a specified period of flying hours or sorties. Thus, Z is Poisson (0.0036) based on flying hours [172/48,337.5 = 0.0036].
Z is Poisson (0.0054) based on sorties [172/32,057 = 0.0054].

Let X be a random variable denoting the number of maintenance actions in a fixed time period of either 60,254.5 flying hours or 38,666 sorties.

Recall, if X has a Poisson distribution with parameter λ, then $E(X) = V(X) = \lambda$.

Flying Hour Based:
If X is approximately Poisson (0.0036 * 60,254.5), the expected value of X is (0.0036)(60,254.5) = 216.916. Also, the variance of X is 216.916, while the standard deviation, σ, is $\sqrt{216.916} = 14.73$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (187,246).

The probability that $(X \leq 187 \text{ or } X \geq 246) = 0.02100 + (1-0.97595) = 0.04505$.

The actual number of 97 maintenance actions experienced from the 1994 F-15C data set for 60,254.5 flying hours is 476. The expected number of 97 maintenance actions is approximately 216. Thus, the residual on the Poisson process based on flying hours is 476 - 216 = 260.

Sortie Based:
If X is approximately Poisson (0.0054 * 38,666), the expected value of X is (0.0054)(38,666) = 208.796. Also, the variance of X is 208.796, while the standard deviation, σ, is $\sqrt{208.796} = 14.45$.

By establishing a +/- 2σ confidence interval, the interval would range from approximately (180,238).

The probability that $(X \leq 180 \text{ or } X \geq 238) = 0.02312 + (1 - 0.97835) = 0.04477$.

The actual number of 97 maintenance actions experienced from the 1994 F-15C data set for 38,666 sorties is 476. The expected number of 97 maintenance actions is approximately 209. Thus, the residual on the Poisson process based on sorties is 476 - 209 = 267.

Hypotheses Testing for Equal Demand Rates Between 1993 and 1994 Data Sets

The two sample, two-tailed F test for equal population variances assumes: 1. Both sampled populations are normally distributed and 2. The samples are random and independent (McClave and Benson, 1988:445). The two-tailed hypotheses test is represented as:

$$H_o: \sigma_1^2 = \sigma_2^2$$
$$H_a: \sigma_1^2 \neq \sigma_2^2$$

However, under the assumption of the Poisson distribution, the mean and variance of a Poisson random variable are both equal to λ (McClave and Benson, 1988:237). Therefore, the two-tailed hypotheses test is equivalent to:

$$H_o: \lambda_{93} = \lambda_{94}$$
$$H_a: \lambda_{93} \neq \lambda_{94}$$

The 93 represents the 1993 data set, while the 94 represents the 1994 data set.

Test Statistic: $F = \dfrac{LargerSampleVariance}{SmallerSampleVariance} = \dfrac{s_1^2}{s_2^2}$ when $s_1^2 > s_2^2$ (or $F = \dfrac{s_2^2}{s_1^2}$ when $s_2^2 > s_1^2$)

Rejection Region: $F > F_{\alpha/2}$ when $s_1^2 > s_2^2$ where $F_{\alpha/2}$ is based on $\nu_1 = n_1 - 1$ and $\nu_2 = n_2 - 1$ degrees of freedom (or $F > F_{\alpha/2}$ when $s_2^2 > s_1^2$ where $F_{\alpha/2}$ is based on $\nu_1 = n_2 - 1$ and $\nu_2 = n_1 - 1$ degrees of freedom (McClave and Benson, 1988:445).

Each two digit work unit code level will now be tested with the two-tailed hypotheses test. For each test, $\alpha = 0.05$, $n_1 = 247$, and $n_2 = 340$. Thus, ν_1 and ν_2 are large enough to approach infinity and $F_{\alpha/2} = F_{0.025} \approx 1.00$ (Appendix B, Table IX, McClave and Benson).

Work Unit Code Level 11:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 237/48,337.5 = 0.0049$

1994 Variance $= s_2^2 = 794/60,254.5 = 0.01318$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01318}{0.0049} = 2.69$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.69 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 237/32,057 = 0.0074$

1994 Variance $= s_2^2 = 794/38,666 = 0.02053$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.02053}{0.0074} = 2.77$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.77 > 1.00$.

Work Unit Code Level 12:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 136/48,337.5 = 0.0028$

1994 Variance $= s_2^2 = 318/60,254.5 = 0.00528$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00528}{0.0028} = 1.89$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.89 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 136/32,057 = 0.0042$

1994 Variance $= s_2^2 = 318/38,666 = 0.00822$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00822}{0.0042} = 1.96$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.96 > 1.00$.

Work Unit Code Level 13:

Flying Hour based: $H_o\!:\!\lambda_{93} = \lambda_{94}$ versus $H_a\!:\!\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 1{,}560/48{,}337.5 = 0.0323$

1994 Variance $= s_2^2 = 2{,}092/60{,}254.5 = 0.0347$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.0347}{0.0323} = 1.07$ because $s_2^2 > s_1^2$.

Result: Reject $H_o\!:\!\lambda_{93} = \lambda_{94}$. Conclude $H_a\!:\!\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.07 > 1.00$.

Sortie Based: $H_o\!:\!\lambda_{93} = \lambda_{94}$ versus $H_a\!:\!\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 1{,}560/32{,}057 = 0.0487$

1994 Variance $= s_2^2 = 2{,}092/38{,}666 = 0.0541$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.0541}{0.0487} = 1.11$ because $s_2^2 > s_1^2$.

Result: Reject $H_o\!:\!\lambda_{93} = \lambda_{94}$. Conclude $H_a\!:\!\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.11 > 1.00$.

Work Unit Code Level 14:

Flying Hour based: $H_o\!:\!\lambda_{93} = \lambda_{94}$ versus $H_a\!:\!\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 314/48{,}337.5 = 0.0065$

1994 Variance $= s_2^2 = 1{,}121/60{,}254.5 = 0.0186$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.0186}{0.0065} = 2.86$ because $s_2^2 > s_1^2$.

Result: Reject $H_o\!:\!\lambda_{93} = \lambda_{94}$. Conclude $H_a\!:\!\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.86 > 1.00$.

Sortie Based: $H_o\!:\!\lambda_{93} = \lambda_{94}$ versus $H_a\!:\!\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 314/32{,}057 = 0.0098$

1994 Variance $= s_2^2 = 1{,}121/38{,}666 = 0.02899$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.02899}{0.0098} = 2.96$ because $s_2^2 > s_1^2$.

Result: Reject $H_o\!:\!\lambda_{93} = \lambda_{94}$. Conclude $H_a\!:\!\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.96 > 1.00$.

Work Unit Code Level 23:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 1{,}023/48{,}337.5 = 0.0212$

1994 Variance $= s_2^2 = 2{,}069/60{,}254.5 = 0.0343$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.0343}{0.0212} = 1.62$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.62 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 1{,}023/32{,}057 = 0.0319$

1994 Variance $= s_2^2 = 2{,}069/38{,}666 = 0.0535$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.0535}{0.0319} = 1.68$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.68 > 1.00$.

Work Unit Code Level 24:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 471/48{,}337.5 = 0.0097$

1994 Variance $= s_2^2 = 1{,}114/60{,}254.5 = 0.01849$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01849}{0.0097} = 1.91$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.91 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 471/32{,}057 = 0.0147$

1994 Variance $= s_2^2 = 1{,}114/38{,}666 = 0.02881$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.02881}{0.0147} = 1.96$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.96 > 1.00$.

Work Unit Code Level 41:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 301/48{,}337.5 = 0.0062$

1994 Variance $= s_2^2 = 667/60{,}254.5 = 0.01107$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01107}{0.0062} = 1.79$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.79 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 301/32{,}057 = 0.0094$

1994 Variance $= s_2^2 = 667/38{,}666 = 0.01725$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01725}{0.0094} = 1.84$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.84 > 1.00$.

Work Unit Code Level 42:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 301/48{,}337.5 = 0.0062$

1994 Variance $= s_2^2 = 766/60{,}254.5 = 0.01271$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01271}{0.0062} = 2.05$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.05 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 301/32{,}057 = 0.0094$

1994 Variance $= s_2^2 = 766/38{,}666 = 0.01981$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01981}{0.0094} = 2.11$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.11 > 1.00$.

Work Unit Code Level 44:

Flying Hour based: $H_o:\lambda_{93}=\lambda_{94}$ versus $H_a:\lambda_{93}\neq\lambda_{94}$

1993 Variance $= s_1^2 = 475/48{,}337.5 = 0.0098$

1994 Variance $= s_2^2 = 665/60{,}254.5 = 0.01104$

Test Statistic: $F=\dfrac{s_2^2}{s_1^2}=\dfrac{0.01104}{0.0098}=1.13$ because $s_2^2>s_1^2$.

Result: Reject $H_o:\lambda_{93}=\lambda_{94}$. Conclude $H_a:\lambda_{93}\neq\lambda_{94}$ because $F>F_{\alpha/2}$ or $1.13>1.00$.

Sortie Based: $H_o:\lambda_{93}=\lambda_{94}$ versus $H_a:\lambda_{93}\neq\lambda_{94}$

1993 Variance $= s_1^2 = 475/32{,}057 = 0.0148$

1994 Variance $= s_2^2 = 665/38{,}666 = 0.01720$

Test Statistic: $F=\dfrac{s_2^2}{s_1^2}=\dfrac{0.01720}{0.0148}=1.16$ because $s_2^2>s_1^2$.

Result: Reject $H_o:\lambda_{93}=\lambda_{94}$. Conclude $H_a:\lambda_{93}\neq\lambda_{94}$ because $F>F_{\alpha/2}$ or $1.16>1.00$.

Work Unit Code Level 45:

Flying Hour based: $H_o:\lambda_{93}=\lambda_{94}$ versus $H_a:\lambda_{93}\neq\lambda_{94}$

1993 Variance $= s_1^2 = 186/48{,}337.5 = 0.0038$

1994 Variance $= s_2^2 = 965/60{,}254.5 = 0.01602$

Test Statistic: $F=\dfrac{s_2^2}{s_1^2}=\dfrac{0.01602}{0.0038}=4.22$ because $s_2^2>s_1^2$.

Result: Reject $H_o:\lambda_{93}=\lambda_{94}$. Conclude $H_a:\lambda_{93}\neq\lambda_{94}$ because $F>F_{\alpha/2}$ or $4.22>1.00$.

Sortie Based: $H_o:\lambda_{93}=\lambda_{94}$ versus $H_a:\lambda_{93}\neq\lambda_{94}$

1993 Variance $= s_1^2 = 186/32{,}057 = 0.0058$

1994 Variance $= s_2^2 = 965/38{,}666 = 0.02496$

Test Statistic: $F=\dfrac{s_2^2}{s_1^2}=\dfrac{0.02496}{0.0058}=4.30$ because $s_2^2>s_1^2$.

Result: Reject $H_o:\lambda_{93}=\lambda_{94}$. Conclude $H_a:\lambda_{93}\neq\lambda_{94}$ because $F>F_{\alpha/2}$ or $4.30>1.00$.

Work Unit Code Level 46:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 284/48{,}337.5 = 0.0058$

1994 Variance $= s_2^2 = 808/60{,}254.5 = 0.01341$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01341}{0.0058} = 2.31$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.31 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 284/32{,}057 = 0.0088$

1994 Variance $= s_2^2 = 808/38{,}666 = 0.02090$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.02090}{0.0088} = 2.38$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.38 > 1.00$.

Work Unit Code Level 47:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 133/48{,}337.5 = 0.0028$

1994 Variance $= s_2^2 = 280/60{,}254.5 = 0.00465$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00465}{0.0028} = 1.66$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.66 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 133/32{,}057 = 0.0041$

1994 Variance $= s_2^2 = 280/38{,}666 = 0.00724$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00724}{0.0041} = 1.77$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.77 > 1.00$.

Work Unit Code Level 49:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 49/48{,}337.5 = 0.0010$

1994 Variance $= s_2^2 = 118/60{,}254.5 = 0.00196$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00196}{0.0010} = 1.96$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.96 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 49/32{,}057 = 0.0015$

1994 Variance $= s_2^2 = 118/38{,}666 = 0.00305$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00305}{0.0015} = 2.03$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.03 > 1.00$.

Work Unit Code Level 51:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 747/48{,}337.5 = 0.0155$

1994 Variance $= s_2^2 = 1{,}043/60{,}254.5 = 0.01731$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01731}{0.0155} = 1.12$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.12 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 747/32{,}057 = 0.0233$

1994 Variance $= s_2^2 = 1{,}043/38{,}666 = 0.02697$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.02697}{0.0233} = 1.16$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.16 > 1.00$.

Work Unit Code Level 52:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 181/48{,}337.5 = 0.0037$

1994 Variance $= s_2^2 = 284/60{,}254.5 = 0.00471$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00471}{0.0037} = 1.27$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.27 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 181/32{,}057 = 0.0056$

1994 Variance $= s_2^2 = 284/38{,}666 = 0.00734$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00734}{0.0056} = 1.31$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.31 > 1.00$.

Work Unit Code Level 55:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 197/48{,}337.5 = 0.0041$

1994 Variance $= s_2^2 = 502/60{,}254.5 = 0.00833$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00833}{0.0041} = 2.03$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.03 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 197/32{,}057 = 0.0061$

1994 Variance $= s_2^2 = 502/38{,}666 = 0.01298$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01298}{0.0061} = 2.13$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.13 > 1.00$.

Work Unit Code Level 57:

Flying Hour based: $H_o\!:\lambda_{93} = \lambda_{94}$ versus $H_a\!:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 61/48{,}337.5 = 0.0013$

1994 Variance $= s_2^2 = 265/60{,}254.5 = 0.00439$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00439}{0.0013} = 3.38$ because $s_2^2 > s_1^2$.

Result: Reject $H_o\!:\lambda_{93} = \lambda_{94}$. Conclude $H_a\!:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $3.38 > 1.00$.

Sortie Based: $H_o\!:\lambda_{93} = \lambda_{94}$ versus $H_a\!:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 61/32{,}057 = 0.0019$

1994 Variance $= s_2^2 = 265/38{,}666 = 0.00685$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00685}{0.0019} = 3.61$ because $s_2^2 > s_1^2$.

Result: Reject $H_o\!:\lambda_{93} = \lambda_{94}$. Conclude $H_a\!:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $3.61 > 1.00$.

Work Unit Code Level 63:

Flying Hour based: $H_o\!:\lambda_{93} = \lambda_{94}$ versus $H_a\!:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 747/48{,}337.5 = 0.0155$

1994 Variance $= s_2^2 = 1{,}057/60{,}254.5 = 0.01754$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01754}{0.0155} = 1.13$ because $s_2^2 > s_1^2$.

Result: Reject $H_o\!:\lambda_{93} = \lambda_{94}$. Conclude $H_a\!:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.13 > 1.00$.

Sortie Based: $H_o\!:\lambda_{93} = \lambda_{94}$ versus $H_a\!:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 747/32{,}057 = 0.0233$

1994 Variance $= s_2^2 = 1{,}057/38{,}666 = 0.02734$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.02734}{0.0233} = 1.17$ because $s_2^2 > s_1^2$.

Result: Reject $H_o\!:\lambda_{93} = \lambda_{94}$. Conclude $H_a\!:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.17 > 1.00$.

Work Unit Code Level 65:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 639/48{,}337.5 = 0.0132$

1994 Variance $= s_2^2 = 771/60{,}254.5 = 0.0128$

Test Statistic: $F = \dfrac{s_1^2}{s_2^2} = \dfrac{0.0132}{0.0128} = 1.03$ because $s_1^2 > s_2^2$.

Result: Accept $H_o:\lambda_{93} = \lambda_{94}$ because $F \approx F_{\alpha/2}$ or $1.03 \approx 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 639/32{,}057 = 0.0199$

1994 Variance $= s_2^2 = 771/38{,}666 = 0.0199$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.0199}{0.0199} = 1.00$ because $s_2^2 = s_1^2$.

Result: Accept $H_o:\lambda_{93} = \lambda_{94}$ because $F = F_{\alpha/2}$ or $1.00 = 1.00$.

Work Unit Code Level 71:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 605/48{,}337.5 = 0.0125$

1994 Variance $= s_2^2 = 1{,}049/60{,}254.5 = 0.0174$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.0174}{0.0125} = 1.39$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.39 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 605/32{,}057 = 0.0189$

1994 Variance $= s_2^2 = 1{,}049/38{,}666 = 0.02713$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.02713}{0.0189} = 1.44$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.44 > 1.00$.

Work Unit Code Level 74:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 2{,}643/48{,}337.5 = 0.0547$

1994 Variance $= s_2^2 = 3{,}710/60{,}254.5 = 0.06157$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.06157}{0.0547} = 1.13$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.13 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 2{,}643/32{,}057 = 0.0824$

1994 Variance $= s_2^2 = 3{,}710/38{,}666 = 0.09595$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.09595}{0.0824} = 1.16$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.16 > 1.00$.

Work Unit Code Level 75:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 464/48{,}337.5 = 0.0096$

1994 Variance $= s_2^2 = 725/60{,}254.5 = 0.01203$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01203}{0.0096} = 1.25$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.25 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 464/32{,}057 = 0.0145$

1994 Variance $= s_2^2 = 725/38{,}666 = 0.01875$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01875}{0.0145} = 1.29$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.29 > 1.00$.

Work Unit Code Level 76:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 974/48{,}337.5 = 0.0201$

1994 Variance $= s_2^2 = 1{,}842/60{,}254.5 = 0.03057$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.03057}{0.0201} = 1.52$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.52 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 974/32{,}057 = 0.0304$

1994 Variance $= s_2^2 = 1{,}842/38{,}666 = 0.04764$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.04764}{0.0304} = 1.57$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $1.57 > 1.00$.

Work Unit Code Level 97:

Flying Hour based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 172/48{,}337.5 = 0.0036$

1994 Variance $= s_2^2 = 476/60{,}254.5 = 0.00790$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.00790}{0.0036} = 2.19$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.19 > 1.00$.

Sortie Based: $H_o:\lambda_{93} = \lambda_{94}$ versus $H_a:\lambda_{93} \neq \lambda_{94}$

1993 Variance $= s_1^2 = 172/32{,}057 = 0.0054$

1994 Variance $= s_2^2 = 476/38{,}666 = 0.01231$

Test Statistic: $F = \dfrac{s_2^2}{s_1^2} = \dfrac{0.01231}{0.0054} = 2.28$ because $s_2^2 > s_1^2$.

Result: Reject $H_o:\lambda_{93} = \lambda_{94}$. Conclude $H_a:\lambda_{93} \neq \lambda_{94}$ because $F > F_{\alpha/2}$ or $2.28 > 1.00$.

References

Abell, John B., Grace M. Carter, Karen E. Isaacson, and Thomas F. Lippiatt. Estimating Requirements for Aircraft Recoverable Spares and Depot Repair. Contract F49620-91-C- 0003. Report R-4210-AR. Santa Monica CA: The RAND Corporation, 1993.

Adams, John L., John B. Abell, and Karen E. Isaacson. Modeling and Forecasting the Demand for Aircraft Recoverable Spare Parts. Contract F49620-91-C-0003. Report R-4211-AF/OSD. Santa Monica CA: The RAND Corporation, 1993.

Blazer, Douglas J. "Computing Leaner, Meaner War Readiness Spares Kits," Air Force Journal of Logistics: 26-28 (Spring 1988).

Brown, B.B. and M.A. Geisler. Analysis of the Demand for B-47 Airframe Parts at Air Base Level. Report RM-1297. Santa Monica CA: The RAND Corporation, July 1954.

Brown, Bernice B. Characteristics of Demand for Aircraft Spare Parts. Report R-292. Santa Monica CA: The RAND Corporation, July 1956.

Campbell, Harrison S. The Relationship of Resource Demands to Airbase Operations. Report RM-3428-PR. Santa Monica CA: January 1963.

Christensen, Bruce P. and Russell E. Ewan, "An Introduction to Reparable Inventory Models and Theory," Research Paper. Air Force Institute of Technology, Wright-Patterson AFB OH, November 1985.

Clarkson, Mary Beth. "How Readiness Spares Packages Are Authorized, Built, and Maintained." Unpublished Report to Headquarters, Air Combat Command (LGSWC), Langley AFB VA, 12 May 1994.

Cooper, Donald R. and C. William Emory. Business Research Methods (Fifth Edition). R.R. Donnelley & Sons Company, 1995.

Crawford, Gordon B. Palm's Theorem for Nonstationary Processes. Report R-2750-RC. Santa Monica CA: The RAND Corporation, October 1981.

Degroot, Morris H. Probability and Statistics. Massachusetts: Addison-Wesley Publishing Company, 1987.

Devore, Jay L. Probability and Statistics for Engineering and the Sciences (Third Edition). California: Brooks/Cole Publishing Company, 1991.

Feeney, G.J. and C.C. Sherbrooke. Systems Analysis and Supply Management. Report RM-4054-PR. Santa Monica CA: The RAND Corporation, April 1964.

-----. The S-1, S Inventory Policy Under Compound Poisson Demand: A Theory of Recoverable Item Stockage. Report RM-4176-PR. Santa Monica CA: The RAND Corporation, March 1966.

Geisler, M.A., B. B. Brown, and O. M. Hixon, Analysis of B-47 Consumption Data and Activity. Report RM-1288. Santa Monica CA: The RAND Corporation, July 1954.

Goldman, T.A. Relationships Between Program Elements and System Demand for Airframe Spare Parts. Report RM-1858. Santa Monica CA: The RAND Corporation, January 1957.

Headquarters, United States Air Force and Logistics Management Institute, "RSP Demand Forecasting Study," Briefing slides. 4 August 1994.

Isaacson, Karen E., Patricia Boren, Christopher L. Tsia, and Raymond Pyles. Dyna-METRIC Version 4: Modeling Worldwide Logistics Support of Aircraft Components. Contract F49620-86-C-0008. Report R-3389-AF. Santa Monica CA: The RAND Corporation, May 1988.

Isaacson, Karen E. and Patricia M. Boren. Dyna-METRIC Version 6: An Advanced Capability Assessment Model. Contract F46920-91-C-0003. Report R-4214-AF. Santa Monica CA: The RAND Corporation, 1993.

McClave, James T. and P.George Benson. Statistics for Business and Economics. San Francisco: Dellen Publishing Company, 1988.

Mitchell, C.R., R.A. Rappold, and W.B. Faulkner. "An Analysis of Air Force EOQ Data With an Application to Reorder Point Calculation," Management Science, 31: 440-446, (April 1983).

Muckstadt, John A. "A Model for Multi-Item, Multi-Echelon, Multi-Indenture Inventory System," Management Science, 20: 472-481, (December 1973).

Myers, Raymond H. Classical and Modern Regression With Applications (Second Edition). Massachusetts: PWS-KENT Publishing Company, 1990.

Neter, John and William Wasserman. Applied Linear Statistical Models: Regression, Analysis of Variance, and Experimental Designs. Illinois: Irwin-Dorsey Limited, 1974.

Page, Gerald L. and John E. Sullivan, "How Do We Know Dyna-METRIC Works: A Look at How We Test Models." Air Force Institute of Technology, unpublished draft report for LOG 290 Combat Capability Assessment Course. Undated.

Pipp, Donald C. "Coronet Warrior: A WRSK Flyout," Air Force Journal of Logistics: 1-4 (Summer 1988).

Rhodes, Jeffery P. "Eagles 17, Bean Counters 4," Air Force Magazine: 74-80 (April 1988).

Sherbrooke, Craig C. A Management Perspective on METRIC - Multi-Echelon Technique for Recoverable Item Control. Report RM-5078/1-PR. Santa Monica CA. The RAND Corporation, January 1968.

-----. "Vari-METRIC: Improved Approximations for Multi-Indenture, Multi-Echelon Availability Models," Operations Research, 34: 311-319 (April 1986).

-----. Optimal Inventory Modeling of Systems: Multi-Echelon Techniques. New York: John Wiley & Sons, Inc., 1992.

Statistix Analytical Software. User's Manual (Version 4.0). Borland International, Inc. and Fleming Software: 1985.

Tedone, Mark J. "Repairable Part Management," Interfaces, 19: 61-68 (July - August 1989).

Youngs, J.W.T., M.A. Geisler, and A.R. Mirkovich. Confidence Intervals for Poisson Parameters in Logistics Research. Report RM-1357. Santa Monica CA: September 1954.

Kephart Vita

Captain Steven D. Kephart is from Sanborn, Pennsylvania. He graduated from the Pennsylvania State University in 1986 with a Bachelor of Science degree in Petroleum and Natural Gas Engineering. After receiving his commission into the United States Air Force through the Officer Training School, Captain Kephart completed the supply operations officer course and was assigned to the 436 Military Airlift Wing, Dover AFB, Delaware.

During his tour at Dover AFB, Captain Kephart filled a variety of supply operations positions in support of the C-5A and C-5B aircraft. These positions included: Assistant, Materiel Management Branch; Chief, Management and Systems Branch; and Fuels Management Officer.

In 1991, he was assigned to Aviano AB, Italy, where he served for one year as the 40 Support Wing Fuels Management Officer. In 1992, Captain Kephart transferred to Headquarters, Sixteenth Air Force, also located at Aviano, and was assigned duties as Chief, Supply and Fuels Operations Division. During his tour at Aviano, Captain Kephart supported operations such as PROVIDE COMFORT, RESTORE HOPE, PROVIDE PROMISE, and DENY FLIGHT. He also received distinction as the 1992 Headquarters, United States Air Forces in Europe Outstanding Fuels Officer.

Upon reassignment from overseas, Captain Kephart entered the Air Force Institute of Technology at Wright-Patterson AFB, Ohio, and graduated in 1995 with a Masters degree in Logistics Management. He was subsequently assigned to the F-15 Systems Program Office, Warner-Robins ALC, Robins AFB, Georgia.

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Roberts Vita

Captain Richard C. Roberts is from Whitehall, Montana graduating from Whitehall High School in 1982. He received a scholarship to study in Denmark where he graduated from Himmelev Gymnasium, Roskilde, Denmark in 1983. Captain Roberts received his Bachelor of Science degree in Business Administration/ Finance from the Montana School of Mineral Science and Technology in 1988. He was enlisted in the Montana Army National Guard, 2/152nd F Troop, as an Armor Calvary Scout. He subsequently was employed at the State Street Bank and Trust in Boston as a Mutual Funds Account Controller before attending Officer Training School in 1989.

Captain Roberts was initially assigned to the 62nd Supply Squadron, McChord AFB, Washington. He deployed to Al Minhad Air Base, United Arab Emirates in August 1990 to support Operations DESERT SHIELD/STORM. As a Second Lieutenant, he was appointed the Chief of Supply for the 388th Tactical Fighter Wing until March 1991. Captain Roberts' next assignment was to San Vito Air Station, Italy in 1991 where he was the Deputy Chief of Supply until the base closed in 1994.

He was accepted into the Air Force Institute of Technology at Wright-Patterson AFB, Ohio in 1994 and graduated with a Masters degree in Logistics Management in 1995. His follow-on assignment was to the Air Force Security Assistance Center at Wright-Patterson AFB. Captain Roberts is married to the former Susan Ann Graham of Falmouth, Massachusetts. They have two children, Sarah and Matthew.

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13. ABSTRACT (Maximum 200 words)

Current Air Force demand forecasting systems, D041 and REALM, assume reparable demand is solely flying hour driven. The purpose of this study is to evaluate the relationship between demands, flying hours, and number of sorties at the work unit code level and improve reparable demand forecasting. A three phase methodology is used to analyze the demand, flying hour, and sortie relationship. The first phase uses multiple regression to determine a relationship at various work unit code levels. Multiple regression provides limited correlation between demands, flying hours, and sorties. The second phase uses Poisson regression to evaluate the integer, count nature of the demands variable used in the analysis. Poisson regression also exhibits poor correlation between demands, flying hours, and sorties. The third phase fits a Poisson process to the data and produces better results than multiple or Poisson regression. However, the Poisson process performs poorly in estimating future demands at the work unit code level, based on historical flying hour and sortie demand rate occurrences. Despite research at the work unit code level, the study results support previous demand forecasting research, which has been unable to demonstrate an accurate demand, flying hour, and sortie relationship.

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